Prognostics and Health Monitoring: Application to Electric Vehicles

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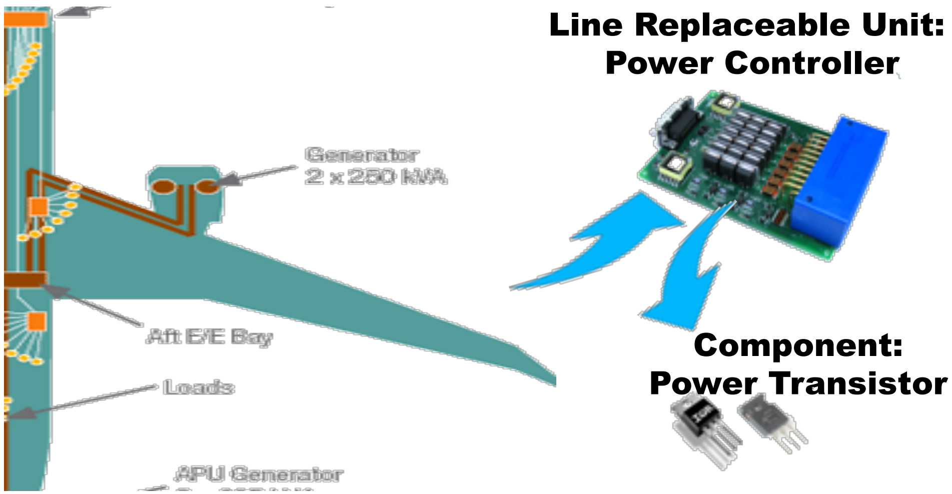
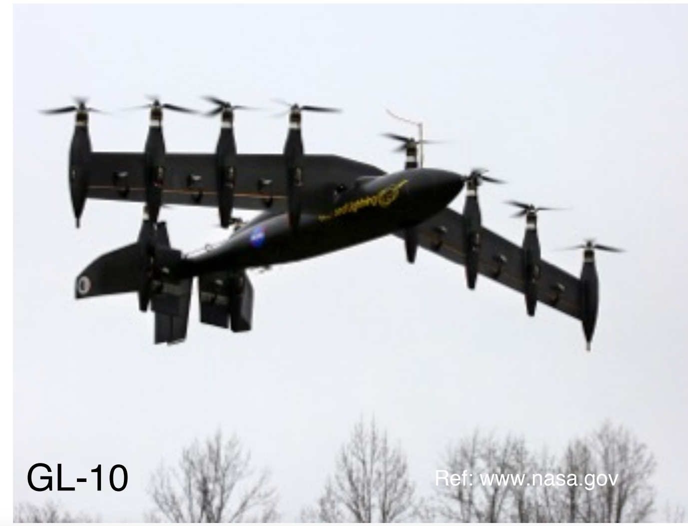
Motivation (1/2)

- Future aircraft systems will rely more on electrical and electronic components
- UAV’s with all electric powertrain are increasingly being used for long missions
- Electrical and Electronic components have increasingly critical role in on-board, autonomous functions for
  - Vehicle controls, communications, navigation, radar systems
  - Power electronic devices such as power MOSFETs and IGBTs are frequently used in high-power switching circuits
  - Batteries are the sole energy storage
  - The integrated navigation (INAV) module combines output of the GPS model and inertial measurement unit.
- Assumption of new functionality increases number of faults with perhaps unanticipated fault modes
- We need understanding of behavior of deteriorated components to develop capability to anticipate failures/predict remaining RUL

Motivation (2/2)

Images courtesy : Boeing





Outline

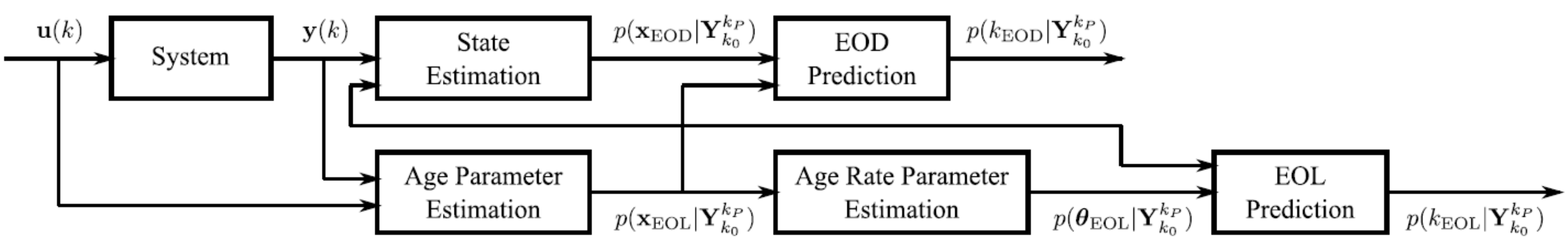
- Goals
  - Understand battery behavior through dynamic models
  - Develop model-based algorithms for state estimation, end of discharge (EOD) prediction, and end of life (EOL) prediction
  - Validate algorithms in the lab and fielded applications
- Algorithms
  - Prognostic Architecture
  - Dynamic state and state-of-charge estimation
- Modeling
  - Electric circuit equivalent (for EOD prediction)
  - Electrochemistry-based model (for EOD and EOL prediction)
- Applications
  - Rover
  - Edge 540-T electric aircraft

Outline

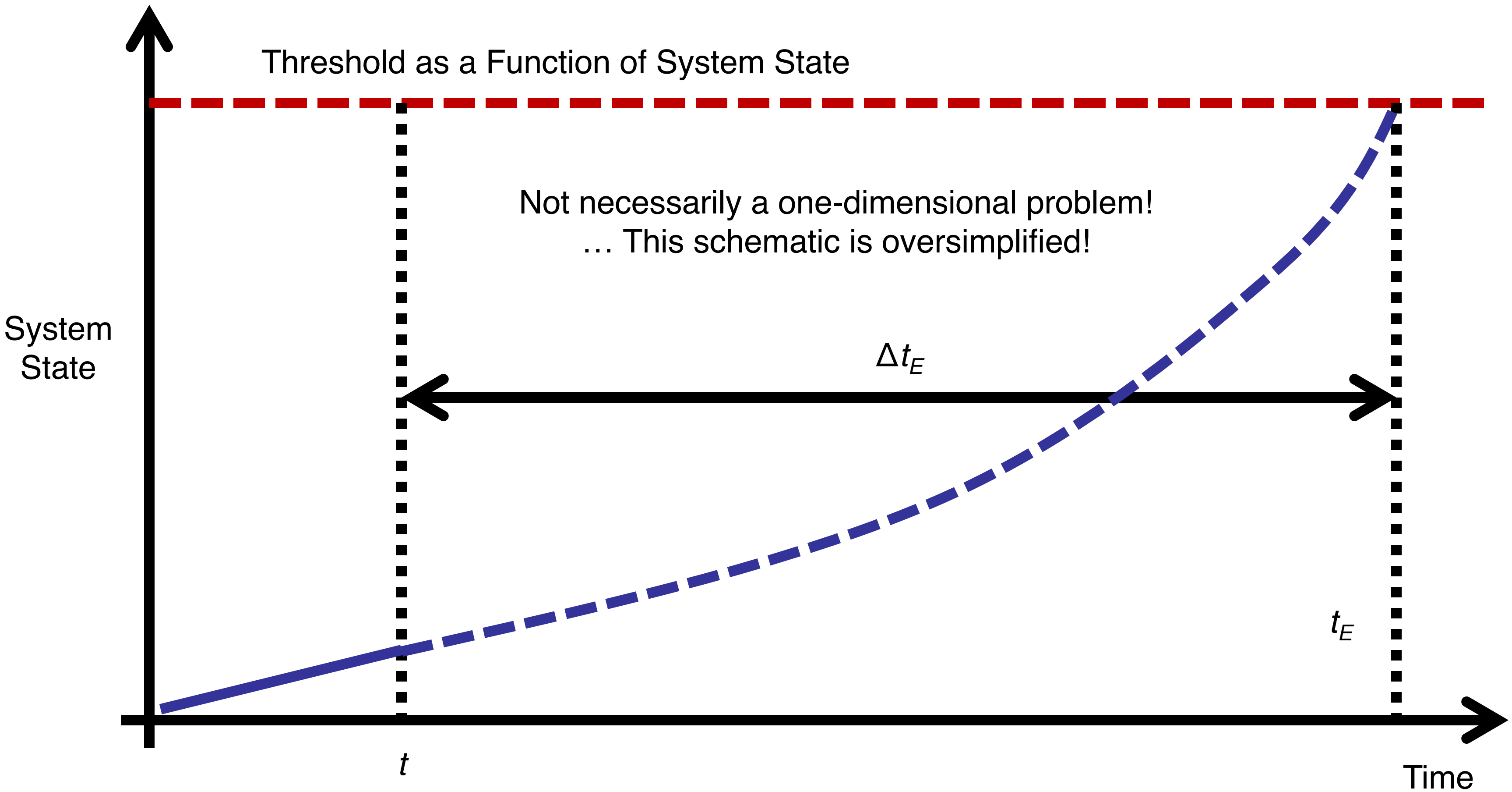
- Introduction to Prognostics
- Introduction to Model-based Prognostics
- Research Approach
- Electric Vehicle Powertrain
- Algorithms
  - Prognostic Architecture
  - Dynamic state and state-of-charge estimation
- Applications
  - Rover
  - Edge 540-T electric aircraft

Integrated Prognostics Architecture

- System (battery) gets inputs (current) and produces outputs (voltage)
- State estimation computes estimate of state given estimates of age parameters
- EOD prediction computes prediction of time of EOD, given state and age parameter estimates
- Age parameter estimation computes estimates of age parameters
- Age rate parameter estimation computes parameters defining aging rate progression
- EOL prediction computes prediction of time of EOL, given age parameter and age rate parameter estimates

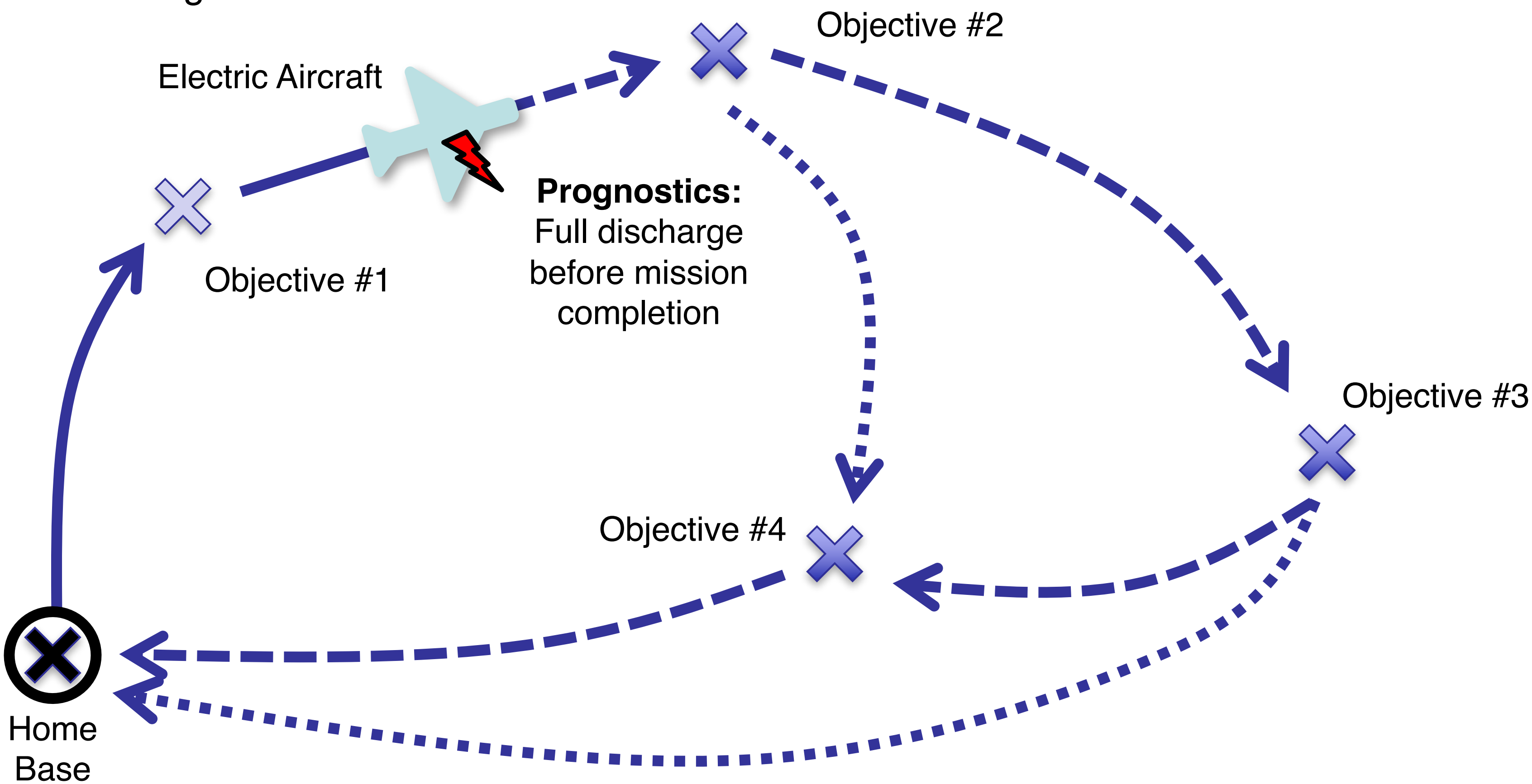


The Basic


Threshold as a Function of System State
Not necessarily a one-dimensional problem!
… This schematic is oversimplified!
System State
Δt_E
t_E
t
Time

Why Prognostics?

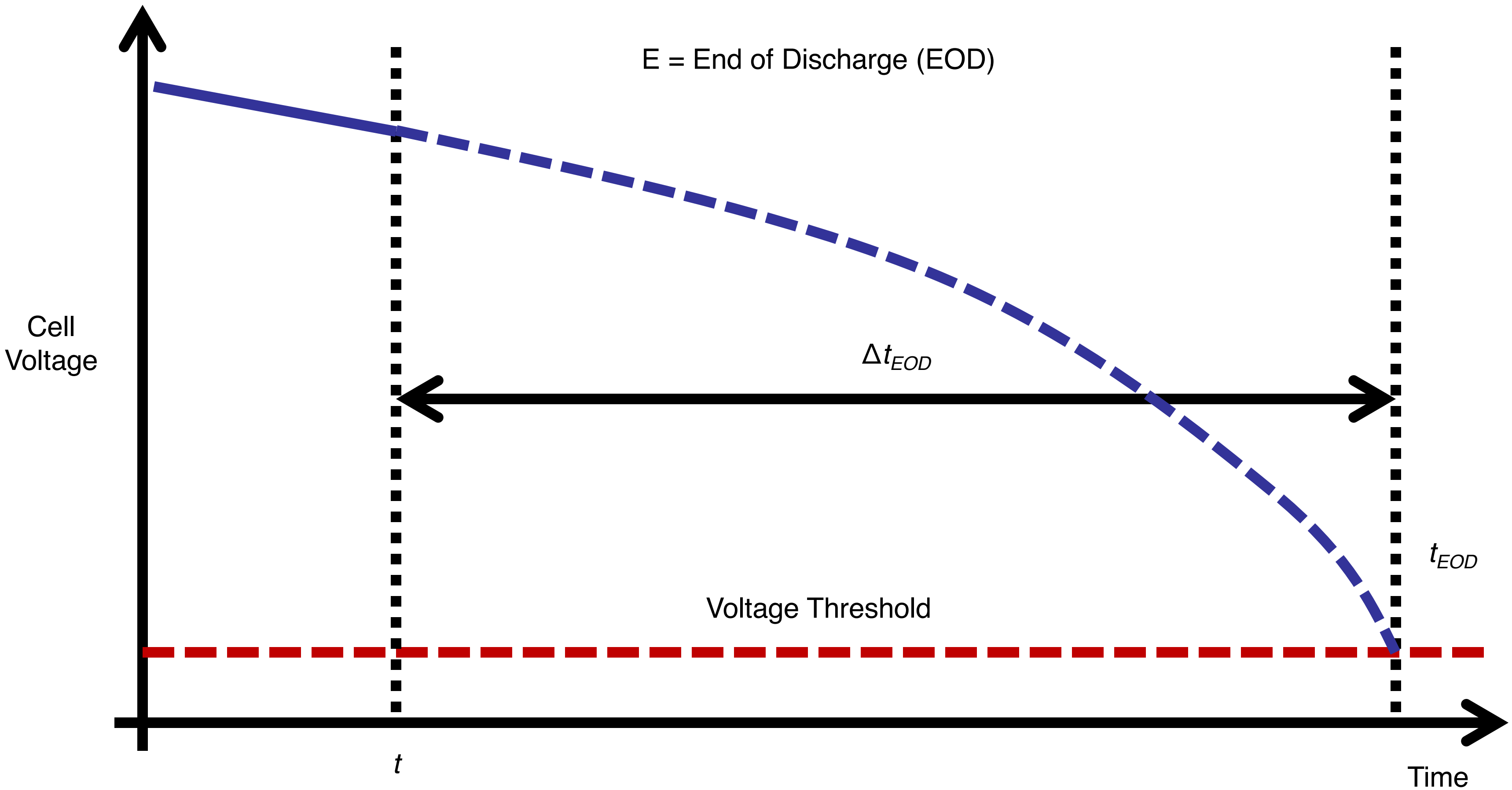
Example: UAV Mission
Visit waypoints to accomplish science objectives. Predict aircraft battery end of discharge to determine which objectives can be met. Based on prediction, plan optimal route. Replan if prediction changes.



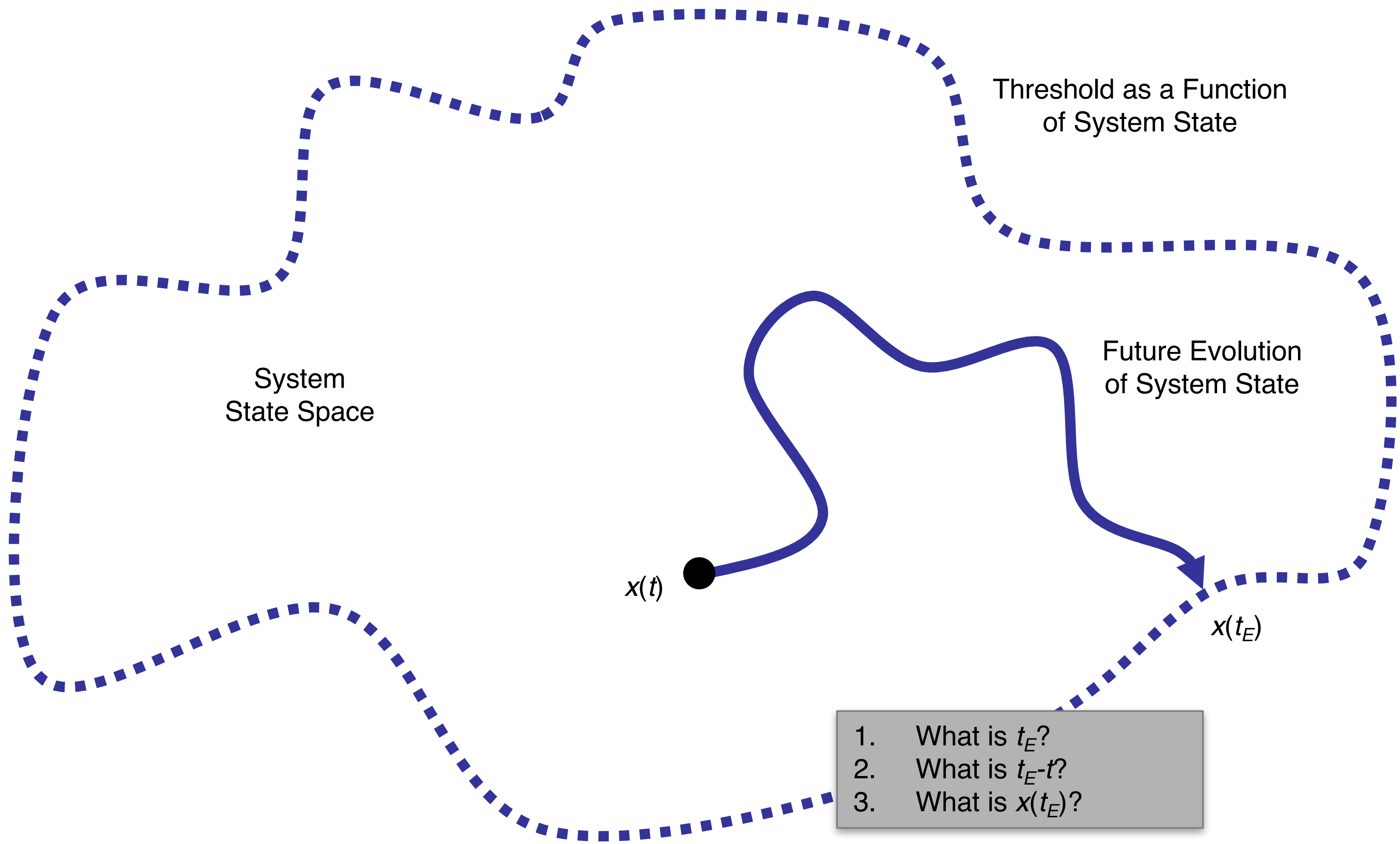
Why Prognostics?

- Prognostics can enable:
  - Adopting condition-based maintenance strategies, instead of time-based maintenance
  - Optimally scheduling maintenance
  - Optimally planning for spare components
  - Reconfiguring the system to avoid using the component before it fails
  - Prolonging component life by modifying how the component is used (e.g., load shedding)
  - Optimally plan or replan a mission
- System operations can be optimized in a variety of ways

The Basic Idea : Batteries Example



The Basic Idea : Batteries Example



1. What is t_E?
2. What is t_E-t?
3. What is $x(t_E)$?

Prognostic Algorithm Categories

- Type I: Reliability Data-based
  - Use population based statistical model
  - These methods consider historical time to failure data which are used to model the failure distribution. They estimate the life of a typical component under nominal usage conditions.
  - Ex: Weibull Analysis

- Type II: Stress-based
  - Use population based fault growth model – learned from accumulated knowledge
  - These methods also consider the environmental stresses (temperature, load, vibration, etc.) on the component. They estimate the life of an average component under specific usage conditions.
  - Ex: Proportional Hazards Model

- Type III: Condition-based
  - Individual component based data-driven model
  - These methods also consider the measured or inferred component degradation. They estimate the life of a specific component under specific usage and degradation conditions.
  - Ex: Cumulative Damage Model, Filtering and State Estimation

Physics-Based Methods

- Description of a system's underlying physics using suitable representation
- Some examples:
  - Model derived from "First Principles"
    - Encapsulate fundamental laws of physics
      - PDEs
      - Euler-Lagrange Equations
  - Empirical model chosen based on an understanding of the dynamics of a system
    - Lumped Parameter Model
    - Classical 1st (or higher) order response curves
  - Mappings of stressors onto damage accumulation
    - Finite Element Model
    - High-fidelity Simulation Model

- Something in the model correlates to the failure mode(s) of interest

Physics-Based Models

- Pros
  - Results tend to be intuitive
    - Based on modeled phenomenon
    - And when they're not, they're still instructive (e.g., identifying needs for more fidelity or unmodeled effects)
  - Models can be reused
    - Tuning of parameters can be used to account for differences in design
  - If incorporated early enough in the design process, can drive sensor requirements (adding or removing)
  - Computationally efficient to implement

- Cons
  - Model development requires a thorough understanding of the system
  - High-fidelity models can be computationally intensive

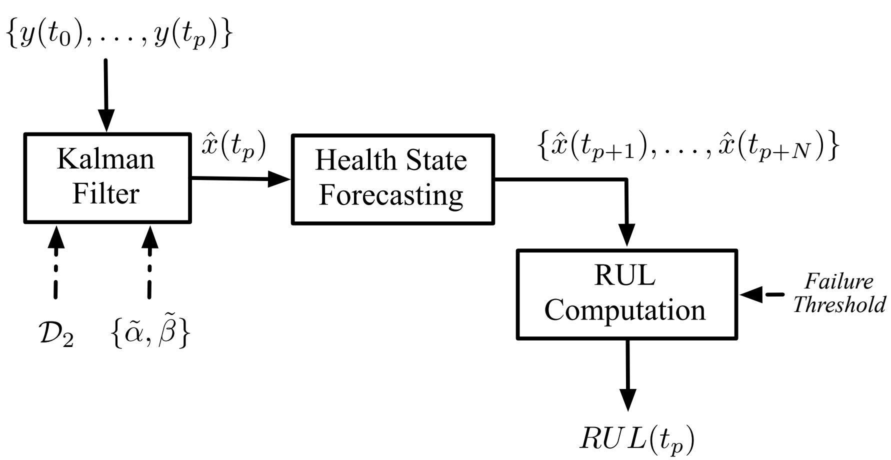
- Examples
  - Paris-Erdogan Crack Growth Model
  - Taylor tool wear model
  - Corrosion model
  - Abrasion model

INTRODUCTION TO MODEL-BASED PROGNOSTICS

Model-based prognostics (1/2)

$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), u(t)) + w(t)$$
$$y(t) = h(\mathbf{x}(t)), u(t)) + v(k)$$

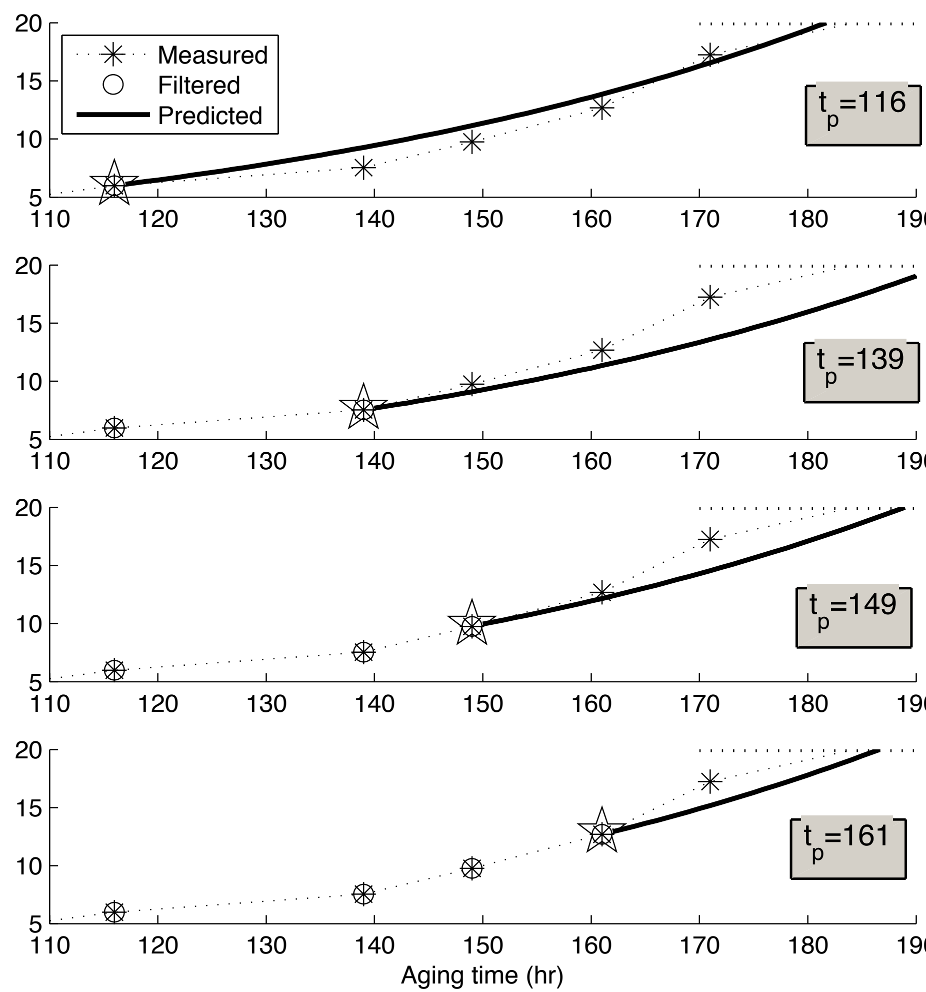
$$R(t_p) = t_{EOL} - t_p$$



- State vector includes dynamics of the degradation process
- It might include nominal operation dynamics
- EOL defined at time in which performance variable cross failure threshold
- Failure threshold could be crisp or also a random variable

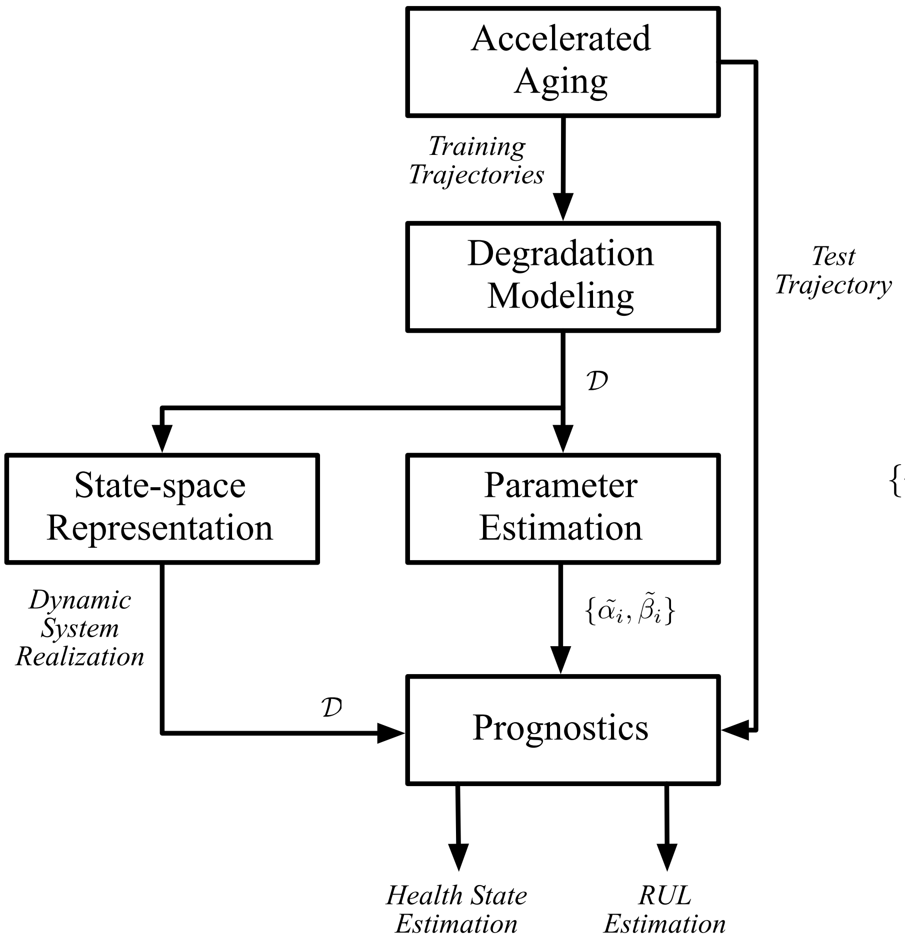
Model-based prognostics (2/2)

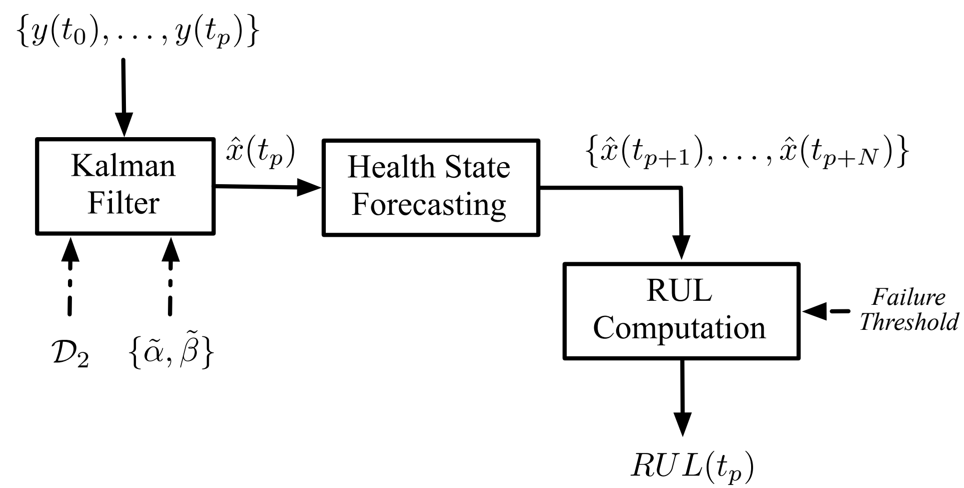
- Tracking of health state based on measurements
- Forecasting of health state until failure threshold is crossed
- Compute RUL as function of EOL defined at time failure threshold is crossed



Methodology

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}$$
$$y_k = Hx_k + v_k$$





RESEARCH APPROACH

High level research efforts

- Prognostics models and algorithms
  - Identification of precursors of failure for MOSFETs under different failure mechanism conditions
  - Identification of precursors of failure for different IGBT technologies (CALCE)
  - Modeling of degradation process MOSFETs
  - Development of prognostics algorithms
- Prognostics for output capacitor in power supplies (Vanderbilt University)
  - Electrical overstress and thermal overstress
  - Development of prognostics algorithms
- Accelerated Life Testing
  - Thermal overstress aging of MOSFETs and IGBTs
  - Electrical overstress aging testbed MOSFETs
  - Electrical overstress aging testbed for Capacitors
- Effects of lightning events of MOSFETS (LaRC)
- Battery Degradation and ageing (ARC – LaRC)
- Ageing Effecting on ESC’s (ARC – LaRC)

Research Approach

Identification of failure modes and their relationship to their particular failure mechanisms

↓

Identification of precursors of failure which play an essential role in the prediction of remaining life

↓

Development of accelerated aging testbeds that facilitate the exploration of different failure mechanisms and aid the understanding of damage progression

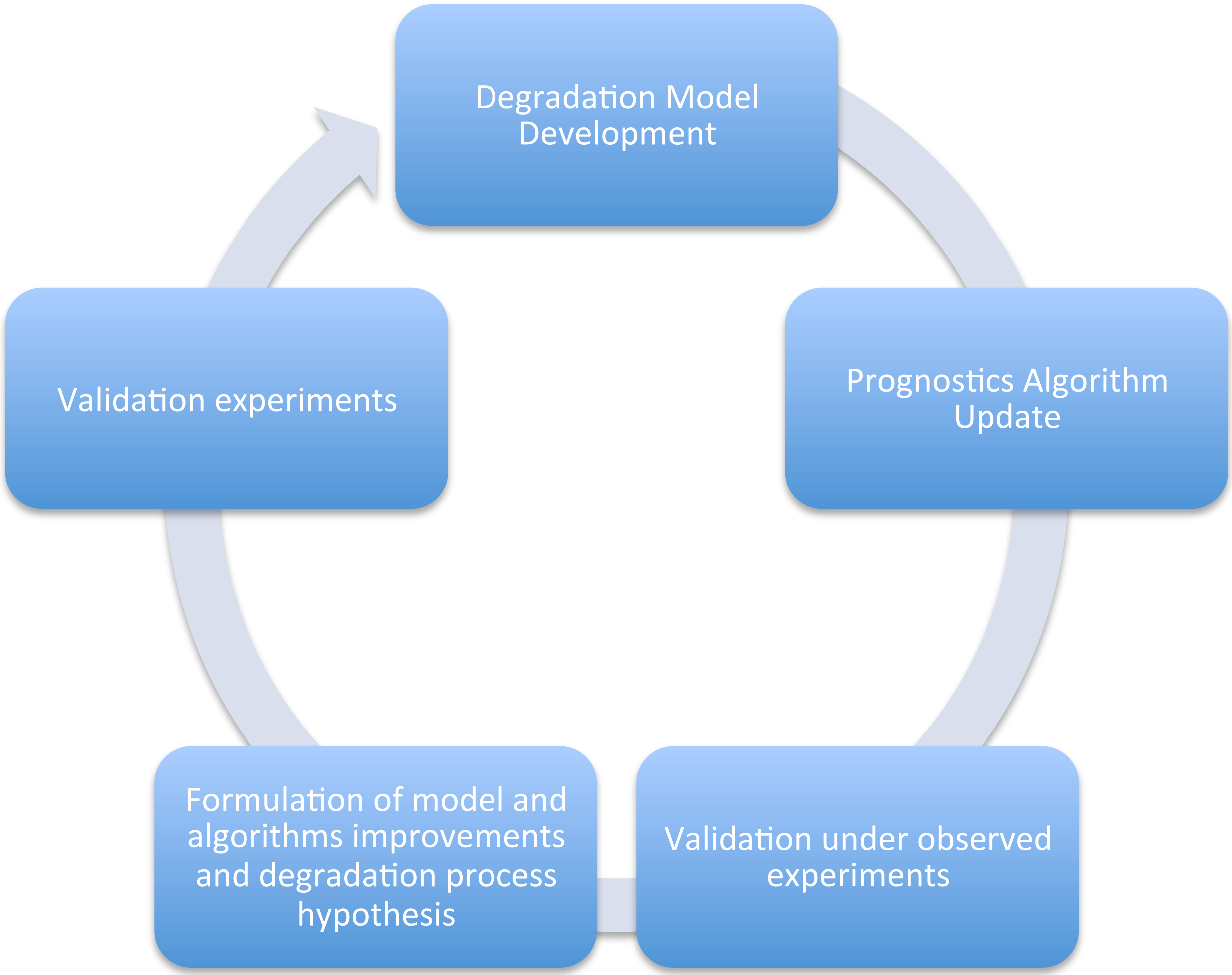
↓

Development of degradation models based on the physics of the device and the failure mechanisms

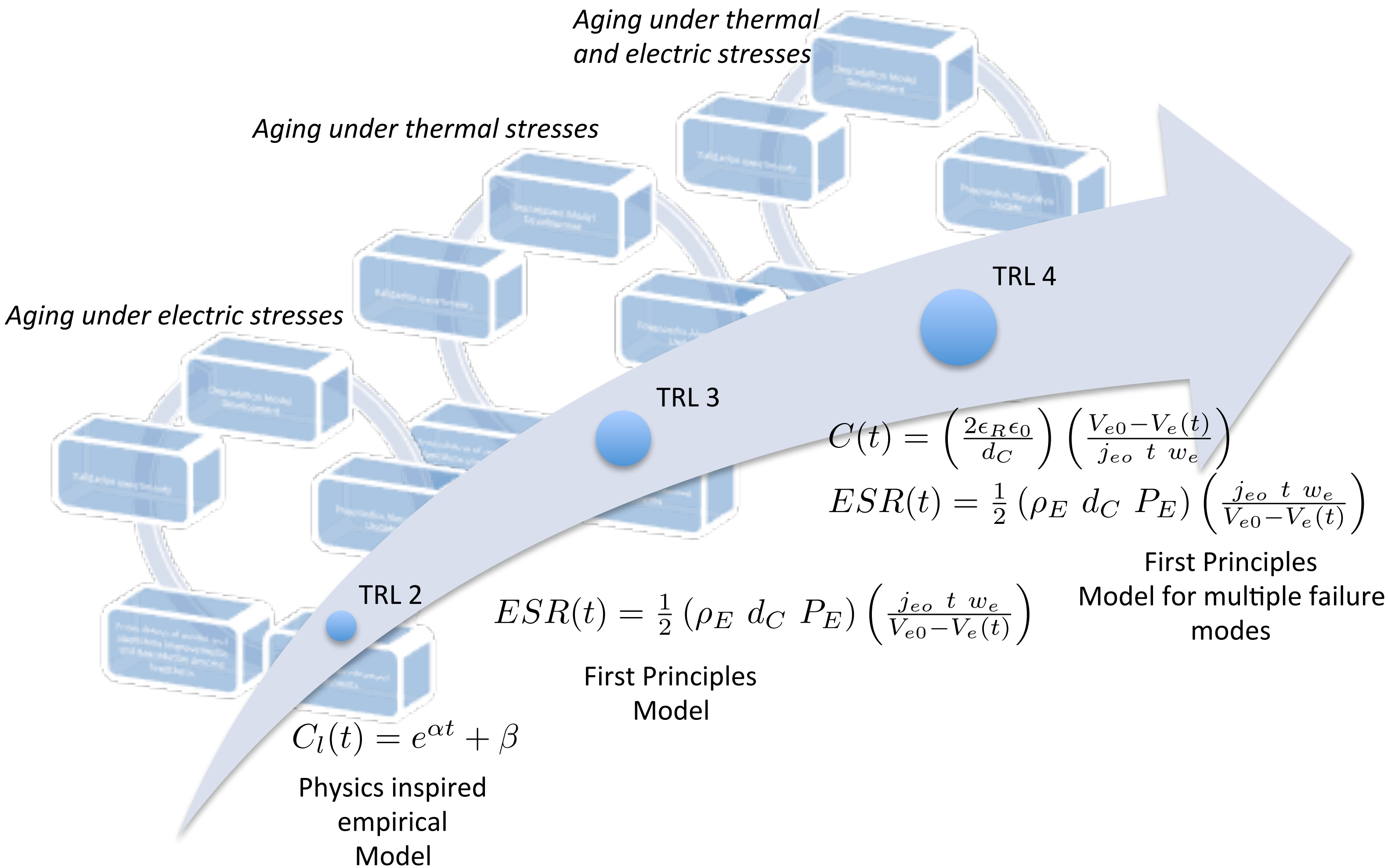
↓

Development of remaining life prediction algorithms that take into account the different sources of uncertainty while leveraging physics-based degradation models that considers future operational and environmental conditions

Prognostics Algorithm Maturation through Validation Experiments

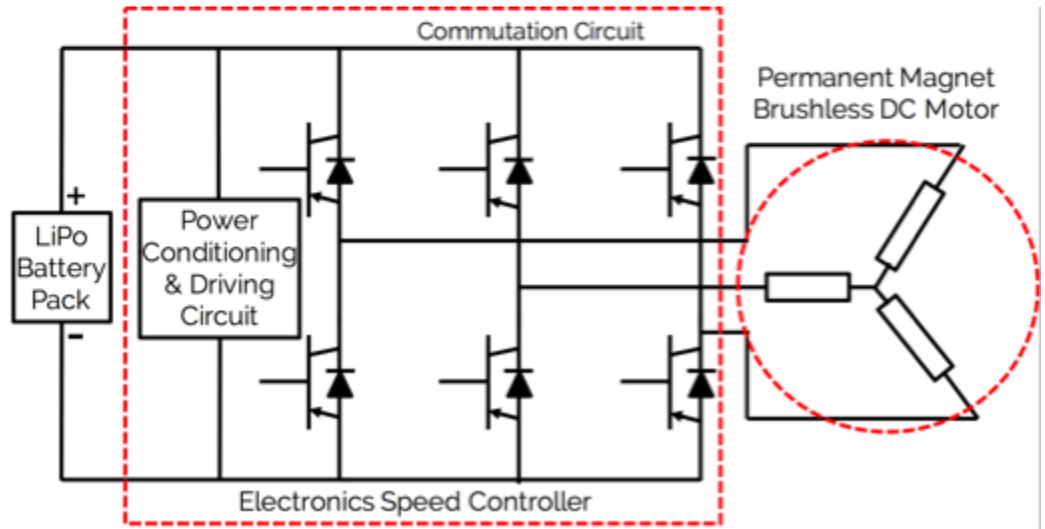


Prognostics Algorithm Maturation through Validation Experiments



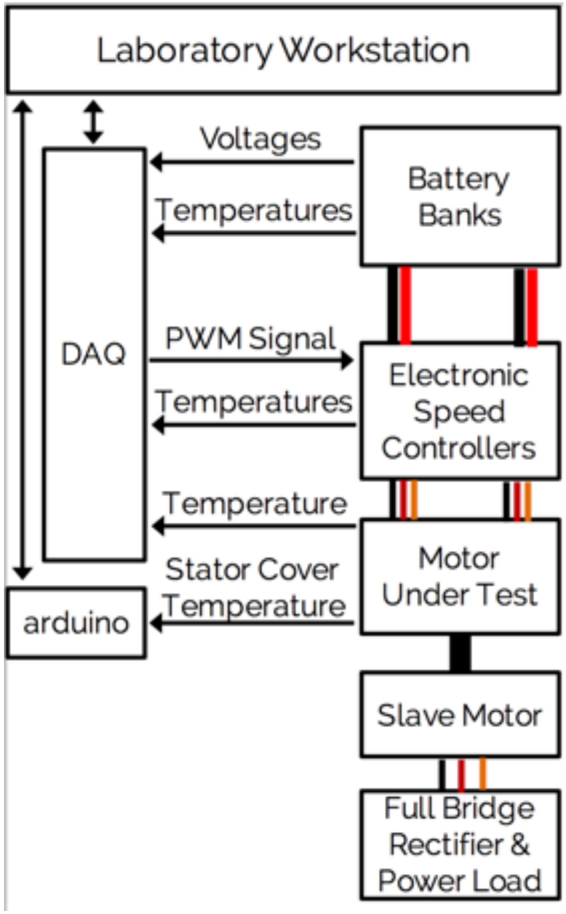
ELECTRIC VEHICLE POWERTRAIN

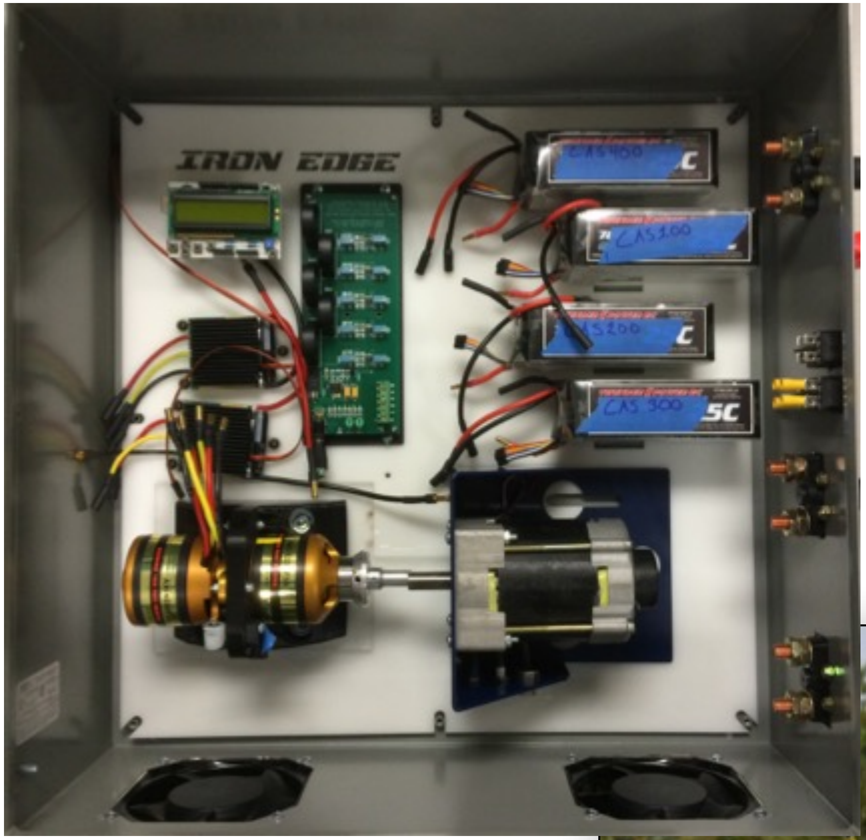
System Level Prognostics



- Component Level Prognostics – System Level Prognostics
  - Batteries
  - Power Conditioning Circuit – Capacitors, MOSFETs
  - Electronic Speed Controllers (ESC) – MOSFETs
  - BLDC
- Study Cascading faults
- Effects of component level aging/degradation on system performance

Hardware in Test Loop





Accelerated Aging

- Traditionally used to assess the reliability of products with expected lifetimes in the order of thousands of hours
  - in a considerably shorter amount of time
- Provides opportunities for the development and validation of prognostic algorithms
- Such experiments are invaluable since run-to-failure data for prognostics is rarely or never available
- Unlike reliability studies, prognostics is concerned not only with time to failure of devices but with the degradation process leading to an irreversible failure
  - This requires in-situ measurements of key output variables and observable parameters in the accelerated aging process with the associated time information
- Thermal, electrical and mechanical overstresses are commonly used for accelerated aging tests of electronics

State Estimation

- What is the current system state and its associated uncertainty?
  - Input: system outputs y from k_0 to k, $y(k_0{:}k)$
  - Output: $p(x(k),\theta(k)|y(k_0{:}k))$
- Battery models are nonlinear, so require nonlinear state estimator (e.g., extended Kalman filter, particle filter, unscented Kalman filter)
- Use unscented Kalman filter (UKF)
  - Straight forward to implement and tune performance
  - Computationally efficient (number of samples linear in size of state space)

Prediction

- Most algorithms operate by simulating samples forward in time until E
- Algorithms must account for several sources of uncertainty besides that in the initial state
  - A representation of that uncertainty is required for the selected prediction algorithm
  - A specific description of that uncertainty is required (e.g., mean, variance)

Prediction Algorithm

- The $\mathtt{P}$ function takes an initial state, and a parameter, an input, and a process noise trajectory
  - Simulates state forward using $\mathbf{f}$ until E is reached to computes k_E for a single sample
- Top-level prediction algorithm calls $\mathtt{P}$
  - These algorithms differ by how they compute samples upon which to call $\mathtt{P}$
- Monte Carlo algorithm ($\mathtt{MC}$) takes as input
  - Initial state-parameter estimate
  - Probability distributions for the surrogate variables for the parameter, input, and process noise trajectories
  - Number of samples, N
- $\mathtt{MC}$ samples from its input distributions, and computes k_E
- The "$\mathtt{construct}$" functions describe how to construct a trajectory given trajectory parameters

Algorithm 1 $k_E(k_P) \leftarrow \mathtt{P}(\mathbf{x}(k_P), \mathbf{\Theta}_{k_P}, \mathbf{U}_{k_P}, \mathbf{V}_{k_P})$

1: $k \leftarrow k_P$
2: $\mathbf{x}(k) \leftarrow \mathbf{x}(k_P)$
3: **while** $T_E(\mathbf{x}(k), \mathbf{\Theta}_{k_P}(k), \mathbf{U}_{k_P}(k)) = 0$ **do**
4: $\quad \mathbf{x}(k+1) \leftarrow \mathbf{f}(k, \mathbf{x}(k), \mathbf{\Theta}_{k_P}(k), \mathbf{U}_{k_P}(k), \mathbf{V}_{k_P}(k))$
5: $\quad k \leftarrow k+1$
6: $\quad \mathbf{x}(k) \leftarrow \mathbf{x}(k+1)$
7: **end while**
8: $k_E(k_P) \leftarrow k$

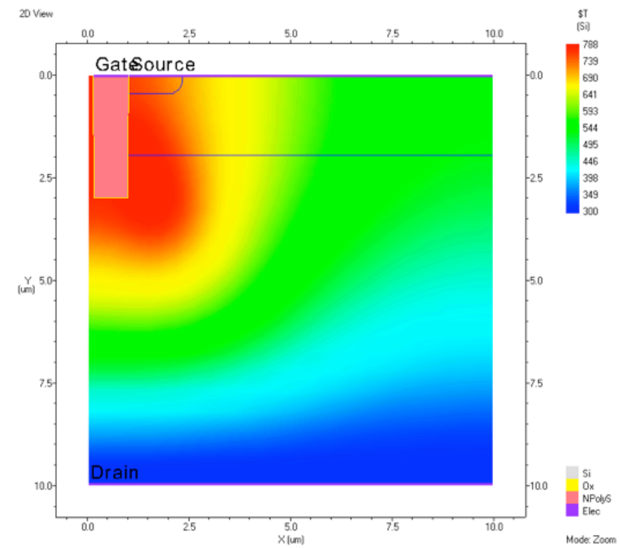
Algorithm 2 $\{k_E^{(i)}\}_{i=1}^N = \mathtt{MC}(p(\mathbf{x}(k_P), \boldsymbol{\theta}(k_P)|\mathbf{y}(k_0{:}k_P)), p(\boldsymbol{\lambda}_\theta), p(\boldsymbol{\lambda}_u), p(\boldsymbol{\lambda}_v), N)$

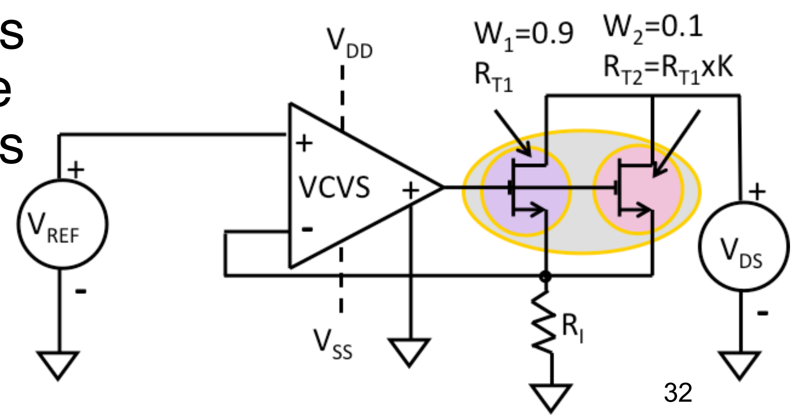
1: **for** $i = 1$ **to** N **do**
2: $\quad (\mathbf{x}^{(i)}(k_P), \boldsymbol{\theta}^{(i)}(k_P)) \sim p(\mathbf{x}(k_P), \boldsymbol{\theta}(k_P)|\mathbf{y}(k_0{:}k_P))$
3: $\quad \boldsymbol{\lambda}_\theta^{(i)} \sim p(\boldsymbol{\lambda}_\theta)$
4: $\quad \mathbf{\Theta}_{k_P}^{(i)} \leftarrow \mathtt{construct\Theta}(\boldsymbol{\lambda}_\theta^{(i)}, \boldsymbol{\theta}^{(i)}(k_P))$
5: $\quad \boldsymbol{\lambda}_u^{(i)} \sim p(\boldsymbol{\lambda}_u)$
6: $\quad \mathbf{U}_{k_P}^{(i)} \leftarrow \mathtt{constructU}(\boldsymbol{\lambda}_u^{(i)})$
7: $\quad \boldsymbol{\lambda}_v^{(i)} \sim p(\boldsymbol{\lambda}_v)$
8: $\quad \mathbf{V}_{k_P}^{(i)} \leftarrow \mathtt{constructV}(\boldsymbol{\lambda}_v^{(i)})$
9: $\quad k_E^{(i)} \leftarrow \mathtt{P}(\mathbf{x}^{(i)}(k_P), \mathbf{\Theta}_{k_P}^{(i)}, \mathbf{U}_{k_P}^{(i)}, \mathbf{V}_{k_P}^{(i)})$
10: **end for**

POWER TRANSISTORS

Modeling for Power MOSFET under electrical overstress

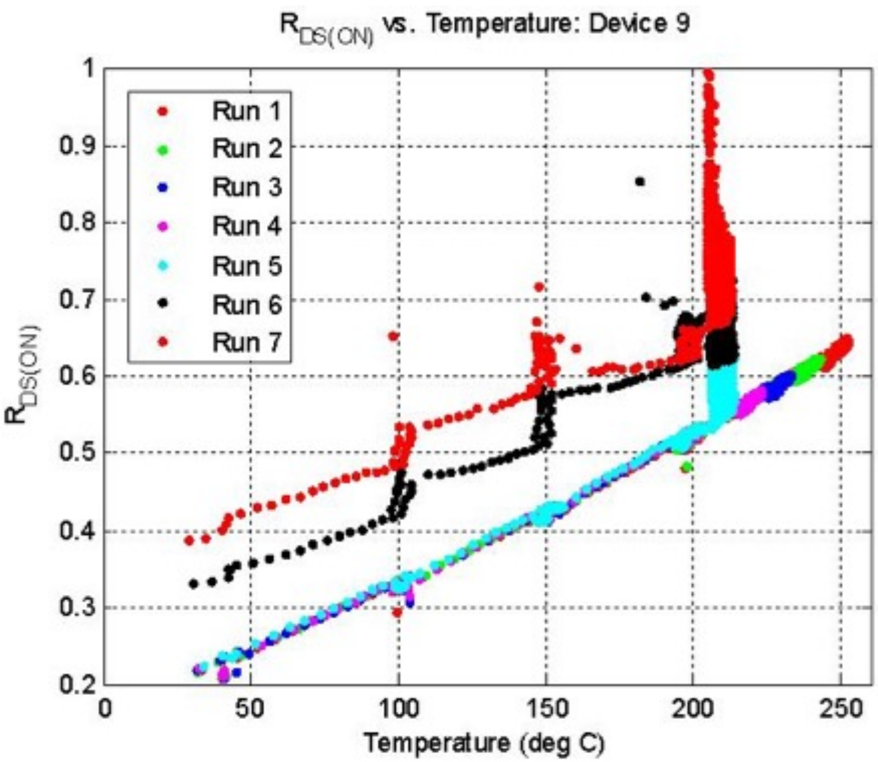
- Two-transistor model is shown to be a good candidate for a degradation model for model-based prognostics.
- The model parameters K, and W1 could be varied as the device degrades as a function of usage time, loading and environmental conditions.
- Parameter W1 defines the area of the healthy transistors, the lower this area, the larger the degradation in the two-transistor model. In addition, parameter K serves as a scaling factor for the thermal resistance of the degraded transistors, the larger this factor, the larger the degradation in the model.





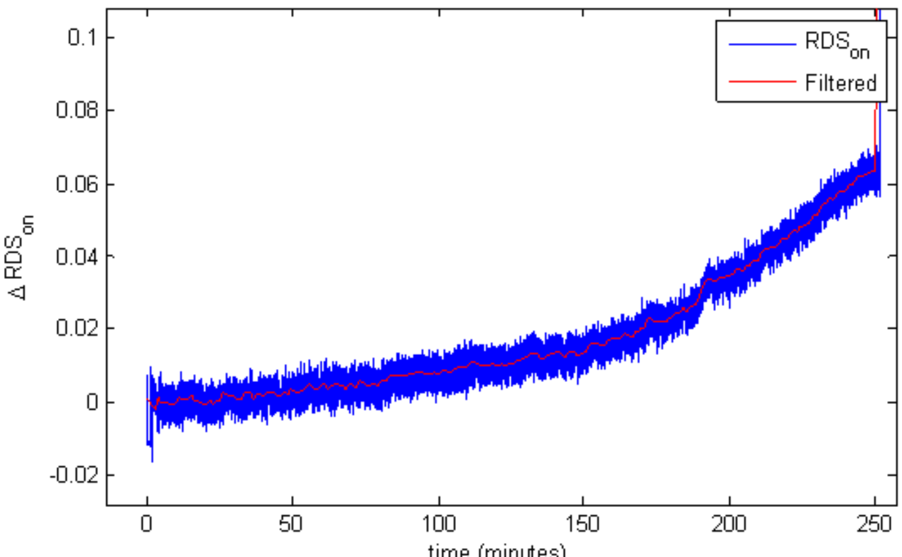
Precursor of Failure

- As case temperature increases, ON-resistance increases
- This relationship shifts as the degradation of the device increases
- For a degraded state, ON-resistance will be higher at any given case temperature
- This is consistent with the die-attach damage since it results on increased junction temperature operation
- This plot can be used directly for fault detection and diagnostics of the die-attach failure mechanism

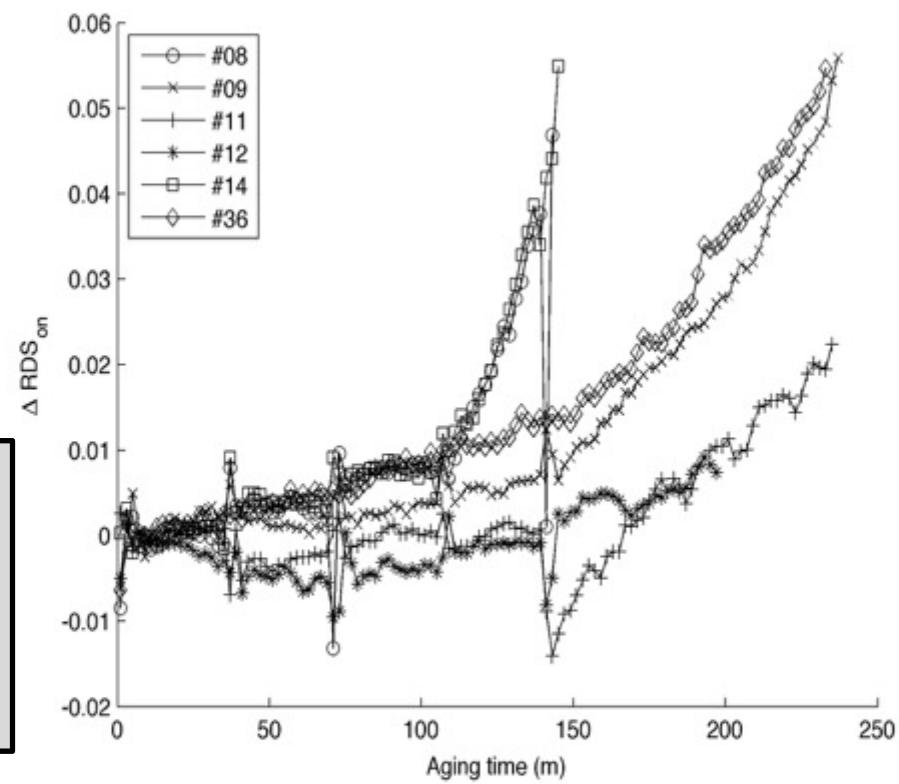


Degradation process data

Normalized ON-state resistance ($\Delta R_{DS(ON)}$) and filtered trajectory for device #36



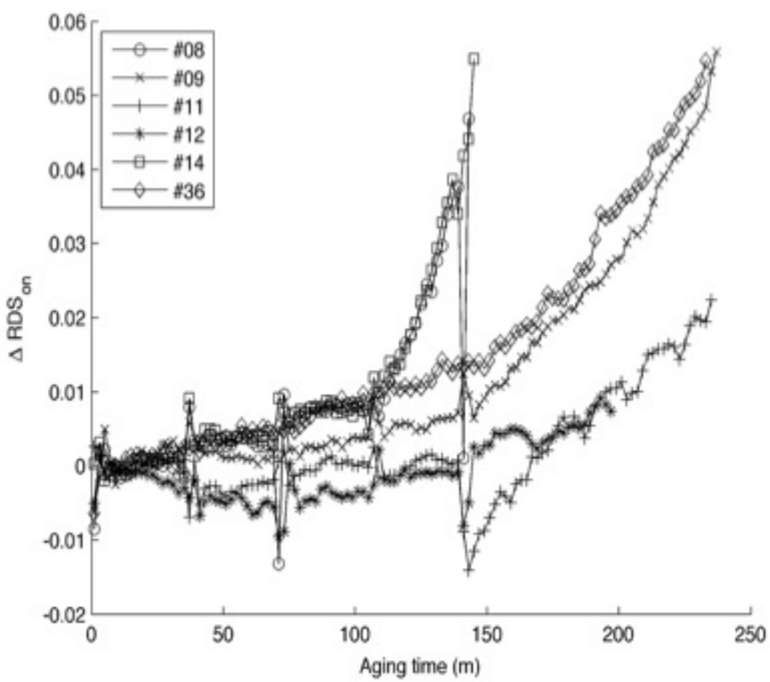
Normalized ON-state resistance ($\Delta R_{DS(ON)}$) and filtered trajectory for device #36



- Cases #08, #09, #11, #12 and #14 are used for algorithm development purposes.
- Case #36 is used to test the algorithms.

Empirical Degradation Model

- An empirical degradation model was selected for the model-based algorithms
- Exponential based function to capture degradation process
- Two parameters in the model which will be estimated on-line



$$\Delta R_{DS(ON)} = \alpha(e^{\beta t} - 1)$$

Prediction of Remaining Life

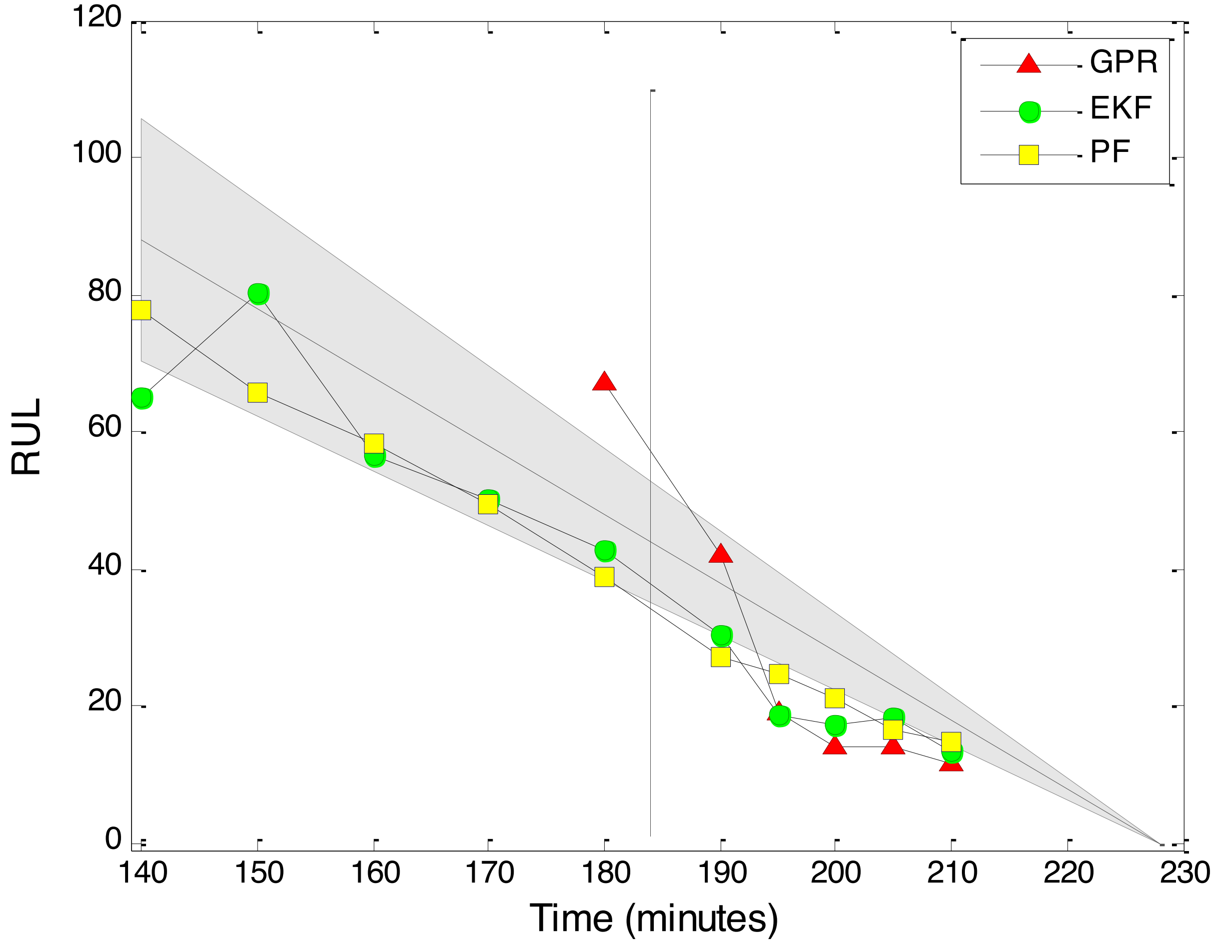
RUL Prediction Methodology Considerations

- A single feature is used to assess the health state of the device ($\Delta R_{DS(ON)}$)
- It is assumed that the die-attached failure mechanism is the only active degradation during the accelerated aging experiment
- Furthermore, $\Delta R_{DS(ON)}$ accounts for the degradation progression from nominal condition through failure
- Periodic measurements with fixed sampling rate are available for $\Delta R_{DS(ON)}$
- A crisp failure threshold of 0.05 increase in $\Delta R_{DS(ON)}$ is used
- The prognostics algorithm will make a prediction of the remaining useful life at time t_p, using all the measurements up to this point either to estimate the health state at time t_p in a regression framework or in a Bayesian state tracking framework
- It is also assumed that the future load conditions do not vary significantly from past load conditions

RUL Prediction Algorithms

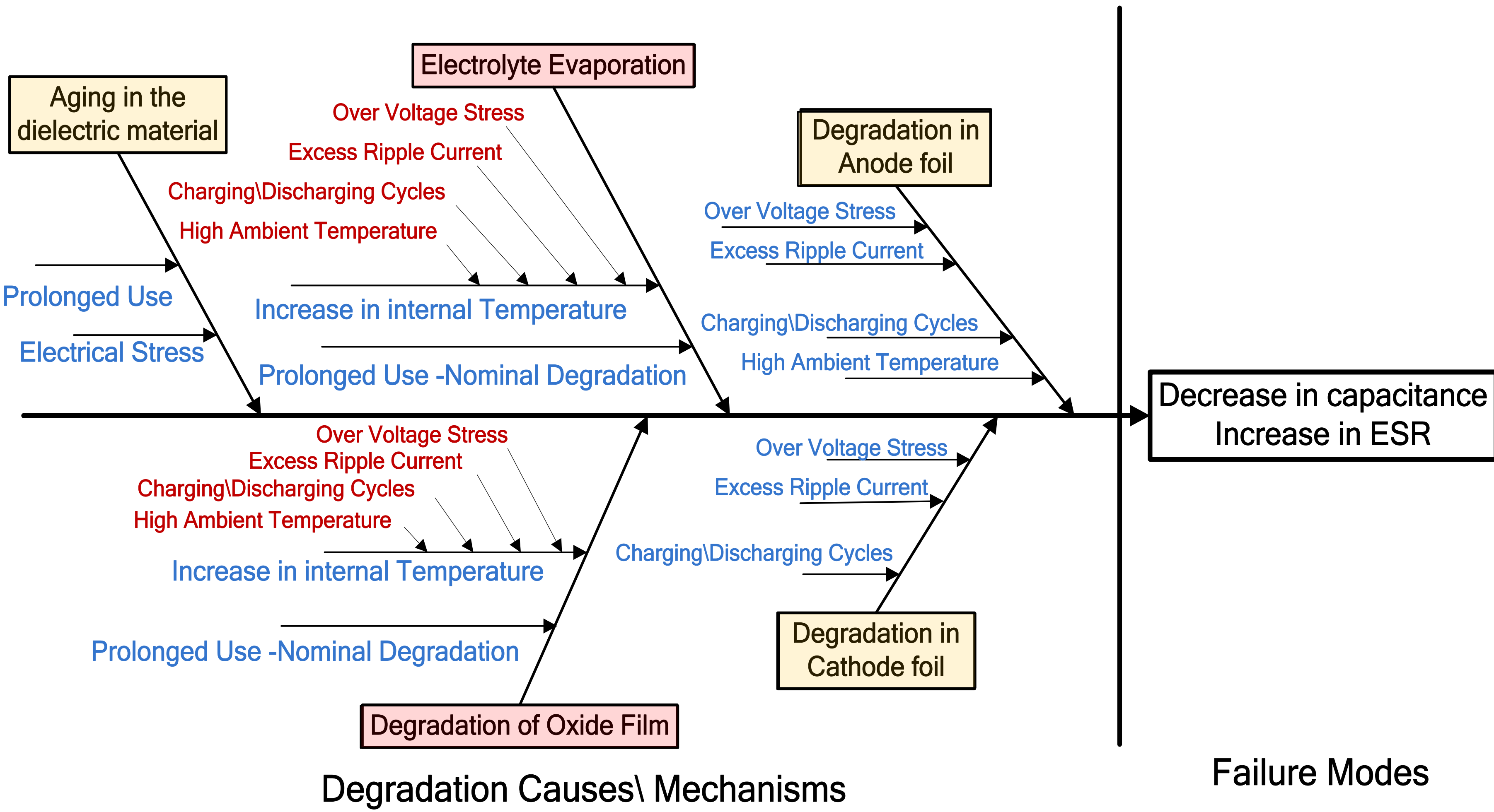
- Gaussian Process Regression
  - Algorithm development cases used to select covariance matrix structure and values
- Extended Kalman filter
  - Empirical degradation model
  - State variable: Normalized ON-resistance and degradation model parameters
  - Arbitrary values for measurement and process noise variance
- Particle filter
  - Empirical degradation model
  - State variable: Normalized ON-resistance, degradation model parameters
  - Exponential growth model used for degradation model parameters
  - Arbitrary values for measurement and process noise variance

RUL estimation results

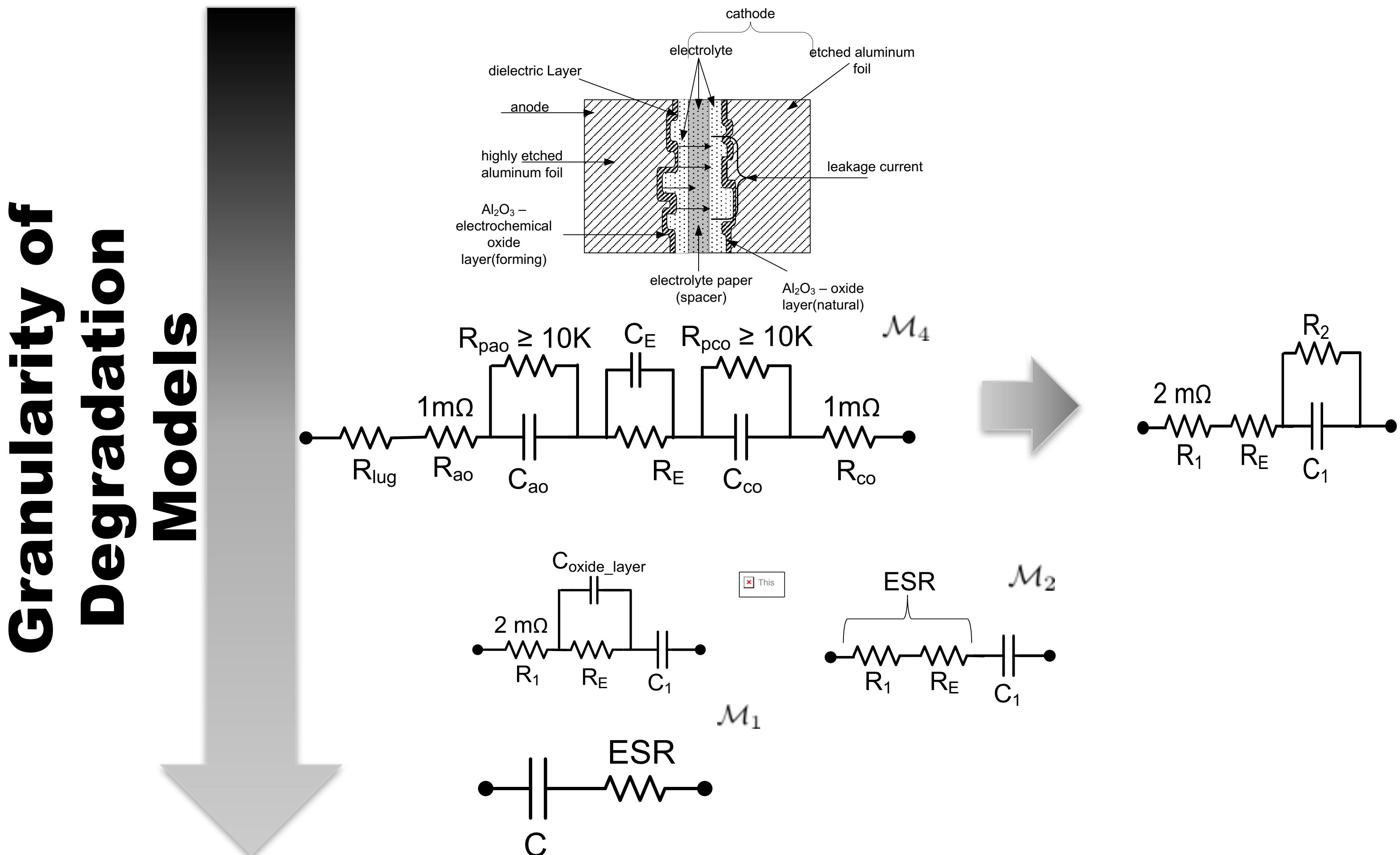


CAPACITORS

Degradation Mechanisms



Degradation Model: Electrical Circuit Equivalent



Capacitance Degradation Model

- Decrease in electrolyte volume :

$$\boxed{Ve(t) = V_{e0} - (w_e A_s j_{eo} t)} \quad (1)$$

where:
V: dispersed volume at time t, V_e: initial electrolyte volume
A_s: surface area of evaporation, j_{eo} : evaporation rate
t : time in minutes, w_e = volume of ethyl glycol molecule

- Capacitance (C)): Physics-Based Model:

$$C = (2\epsilon_R \epsilon_O A_s)/d_C \quad (2)$$

- Electrolyte evaporation dominant degradation phenomenon
  – First principles: Capacitance degradation as a function of electrolyte loss

$$\mathcal{D}_1 : C(t) = \left(\frac{2\epsilon_R \epsilon_0}{d_C}\right)\left(\frac{V_{e0} - V_e(t)}{j_{eo}\ t\ w_e}\right), \quad (3)$$

where:
C : capacitance of the capacitor,
ϵ_R : relative dielectric constant,
ϵ_O : permittivity of free space,
d_C : oxide thickness.

Capacitance Degradation Model

- Oxide breakdown observed - experimental data
- The breakdown factor is exp. function of electrolyte evaporation

$$C_{bk(t)} = \exp f(V_{eo} - V_{e(t)})$$

- Updated in capacitance degradation model :

$$\boxed{\begin{gathered} C = (2\epsilon_R \epsilon_0 A_s c_{bk})/d_C, \\ \mathcal{D}_{11} : C(t) = c_{bk(t)} \left(\frac{2\epsilon_R \epsilon_0}{d_C} \right) \left(\frac{V_{e0} - V_e(t)}{j_{eo}\ t\ w_e} \right) \end{gathered}}$$

Dynamic Model of ESR

- Decrease in electrolyte volume :

$$Ve(t) = V_{e0} - (w_e A_s j_{eo} t)$$

- ESR
  - Based on mechanical structure and electrochemistry.
  - With changes in R_E (electrolyte resistance)

$$ESR = \frac{1}{2}\left(\frac{\rho_E d_C P_E e_{bk(t)}}{A_s}\right)$$

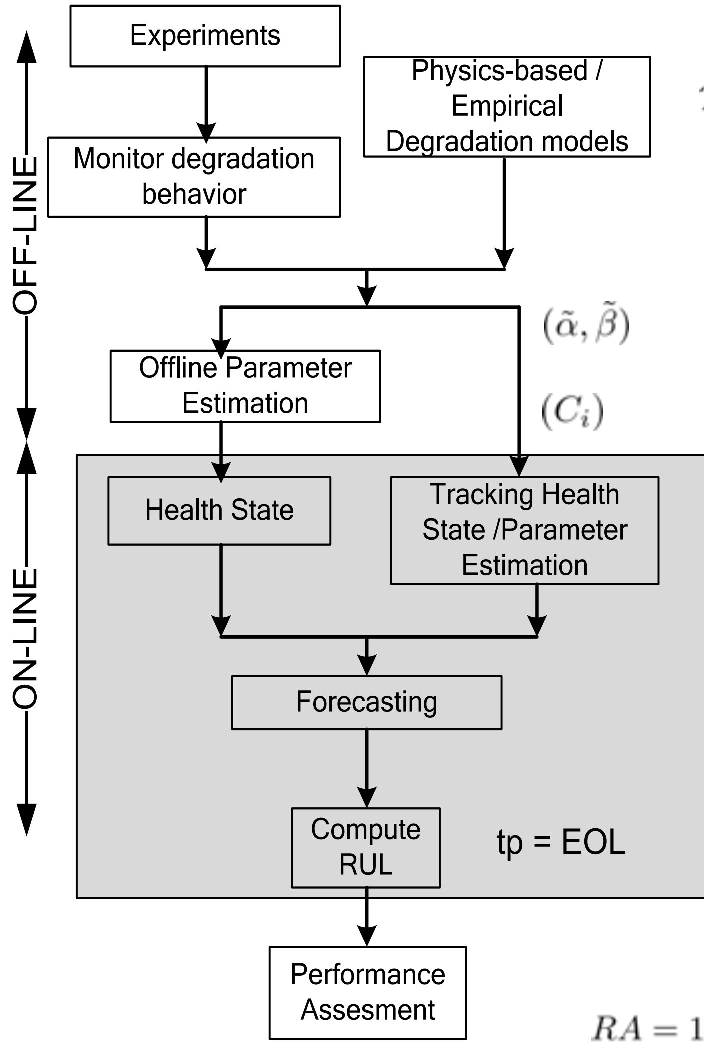
$$\mathcal{D}_2 : ESR(t) = \frac{1}{2}(\rho_E \; d_C \; P_E)\left(\frac{j_{eo} \; t \; w_e e_{bk(t)}}{V_e(t)}\right) \qquad (8)$$

Dynamic ESR degradation Model :

$$\mathcal{D}_5 : \frac{1}{ESR_{k+1}} = \frac{1}{ESR_k} - \left(\frac{2 w_e A_s j_{eo}}{\rho_E \; P_E \; d_C^2 \; e_{bk(t)}}\right)\Delta t$$

where:
ρ_E : electrolyte resistivity,
P_E : correlation factor related to electrolyte spacer porosity and average liquid pathway,
$e_{bk(t)}$: resistance dependence oxide breakdown factor

Process Flow



$$\mathcal{D}_1 : C(t) = \left(\frac{2\epsilon_R \epsilon_0 c_{bk}}{d_C}\right)\left(\frac{V_0 - V_e(t)}{j_{eo}\ t\ w_e}\right)$$

$$(\tilde{\alpha}, \tilde{\beta})$$

$$(C_i)$$

$$\mathcal{D}_4 : C_{k+1} = C_k - \left(\frac{2\epsilon_R \epsilon_0 w_e A_s j_{eo} c_{bk}}{d_C^2}\right)\Delta t,$$

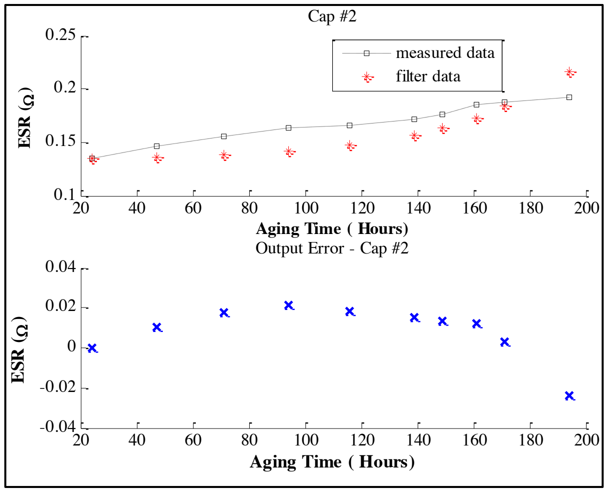
$$(C_i, j_{eo(i)}, c_{bk(i)})$$

$$(C)$$

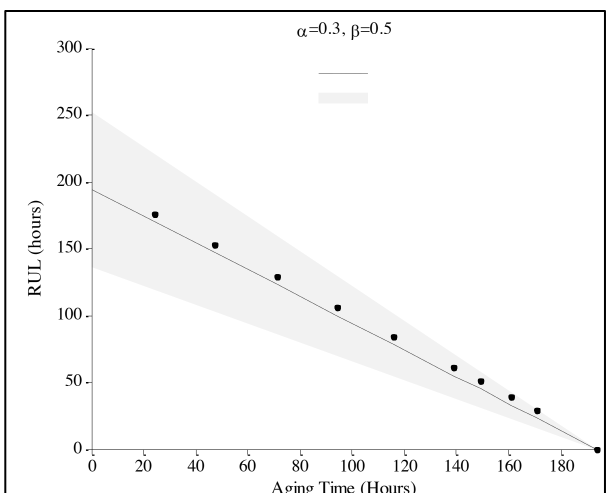
$$RA = 100\left(1 - \frac{RUL^* - RUL}{RUL^*}\right)$$

RUL and Validation – EOS -Experiment – ESR Degradation Model $\mathcal{D}_5$

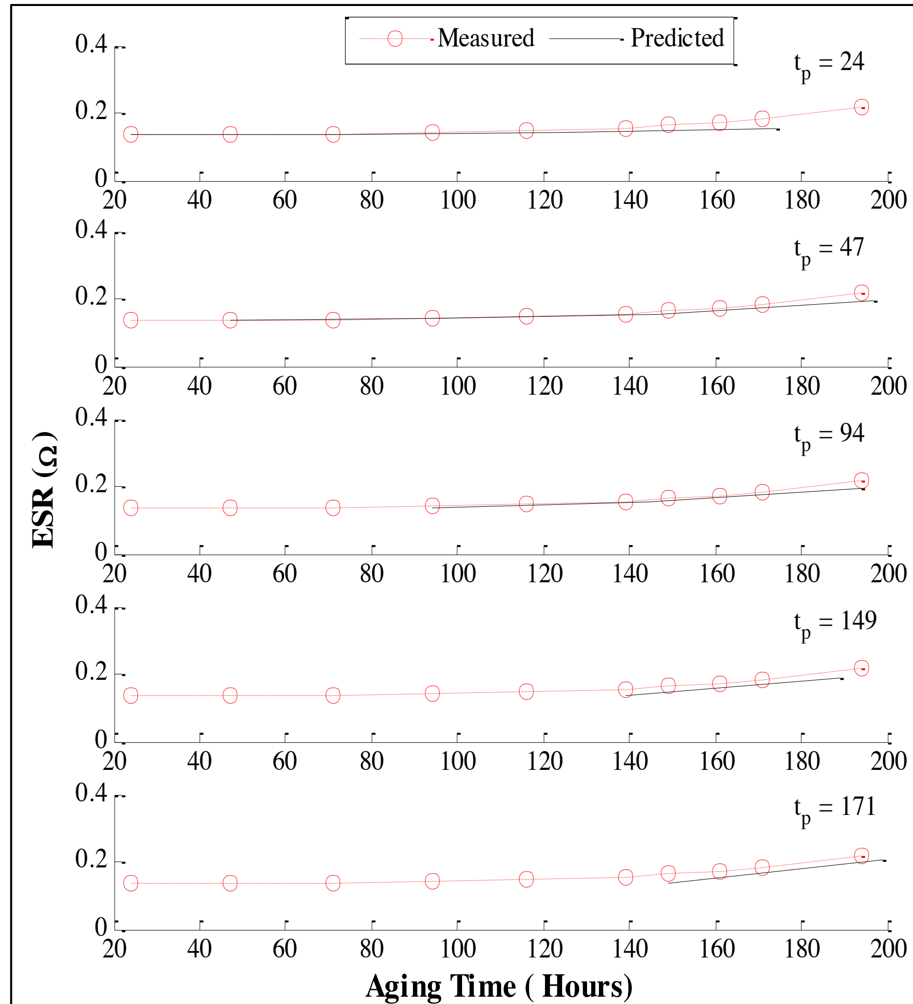
Tracking



Alpha Lambda

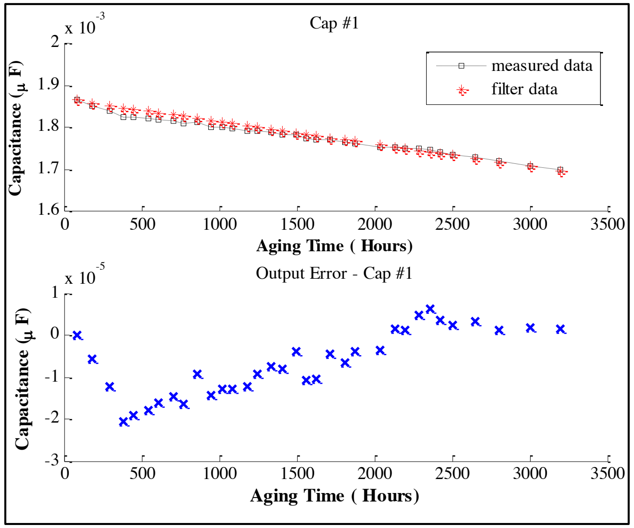


Predictions at different aging time

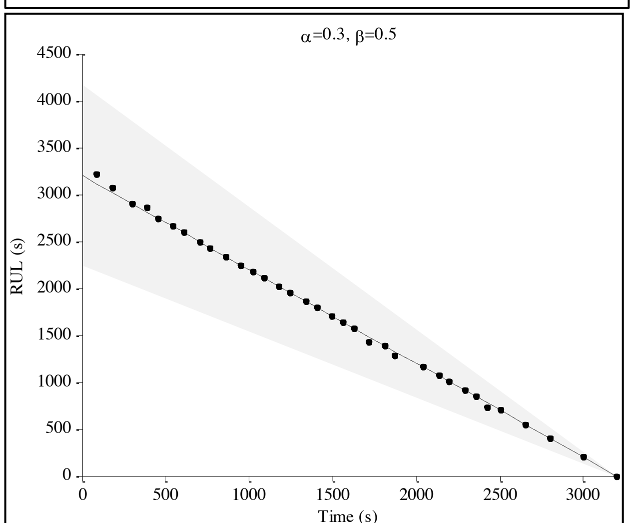


RUL and Validation – TOS -Experiment - Capacitance

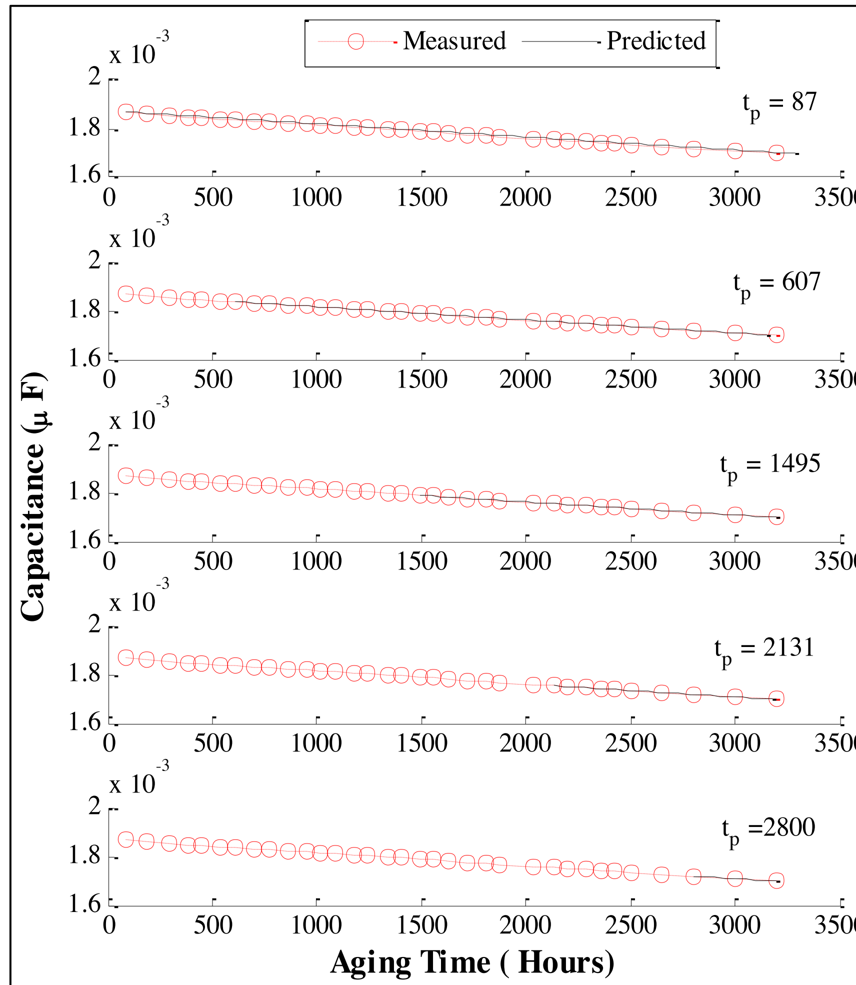
Tracking



Alpha Lambda



Predictions at different aging time

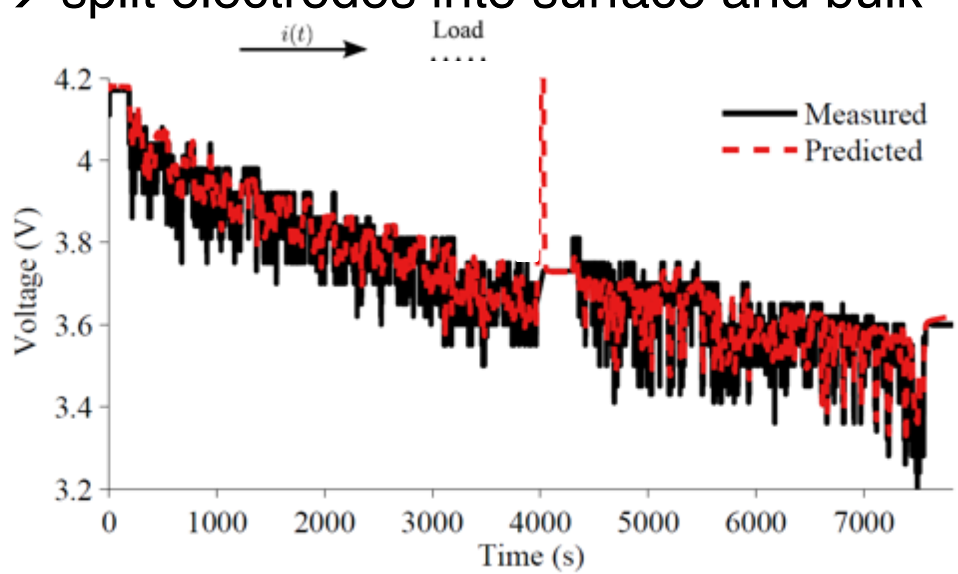


LI- ION BATTERIES

Electrochemical Li-ion Model

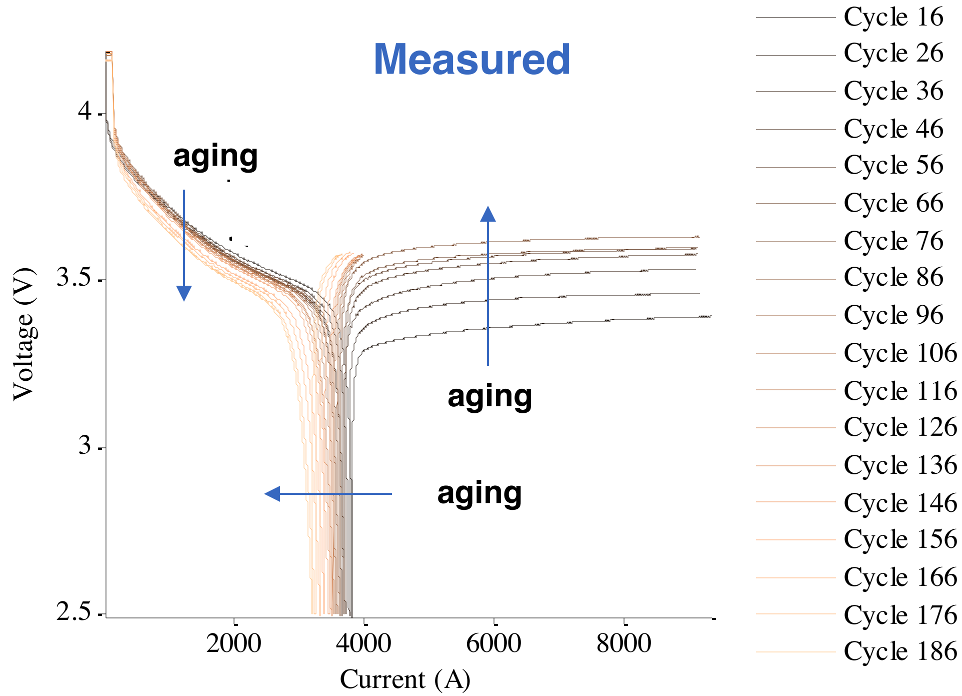
- <u>Electrochemical Models vs. Empirical Models</u>
  - Battery physics models enable more direct representation of age-related changes in battery dynamics than empirical models
  - Typically have a higher computational cost and more unknown parameters

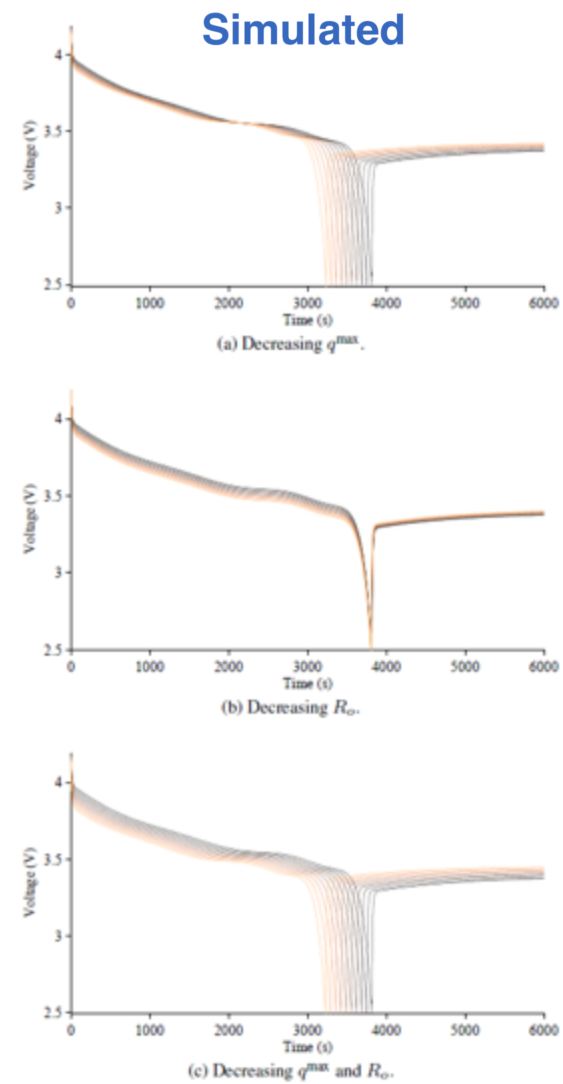
- Lumped-parameter, ordinary differential equations
- Capture voltage contributions from different sources
  - Equilibrium potential → Nernst equation with Redlich-Kister expansion
  - Concentration overpotential → split electrodes into surface and bulk control volumes
  - Surface overpotential → Butler-Volmer equation applied at surface layers
  - Ohmic overpotential → Constant lumped resistance accounting for current collector resistances, electrolyte resistance, solid-phase ohmic resistances



Battery Aging

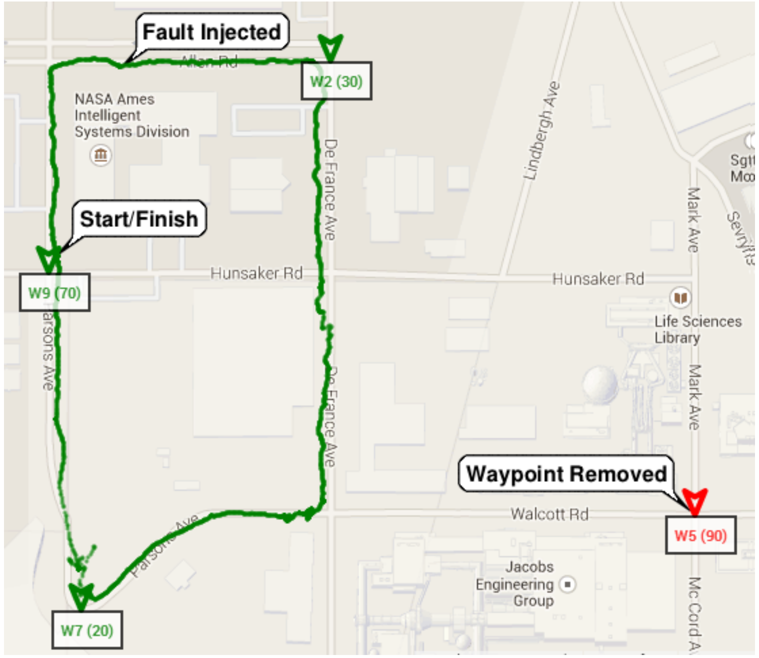
- Contributions from both decrease in mobile Li ions (lost due to side reactions related to aging) and increase in internal resistance
  - Modeled with decrease in "q^{max}" parameter, used to compute mole fraction
  - Modeled with increase in "R_o" parameter capturing lumped resistances





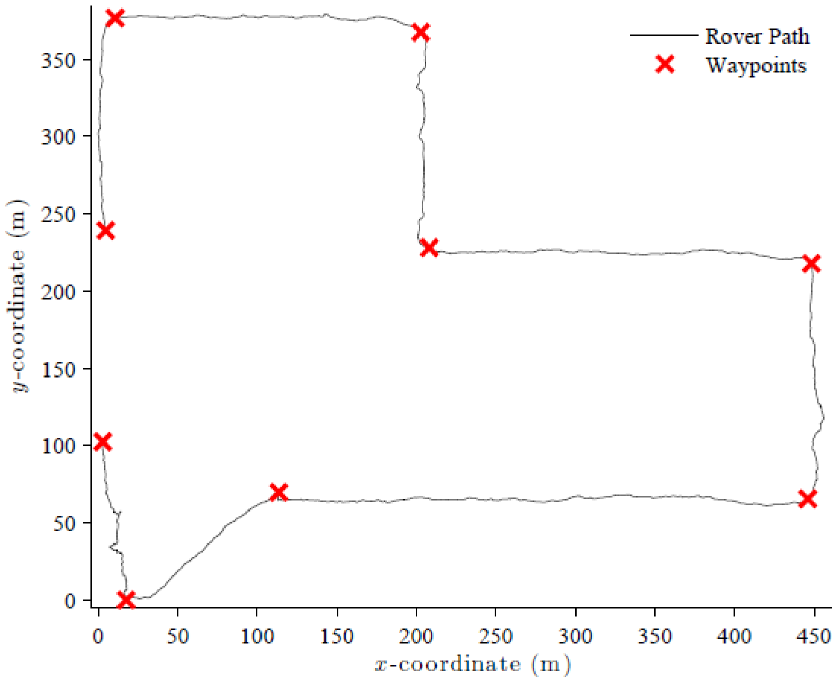
Rover

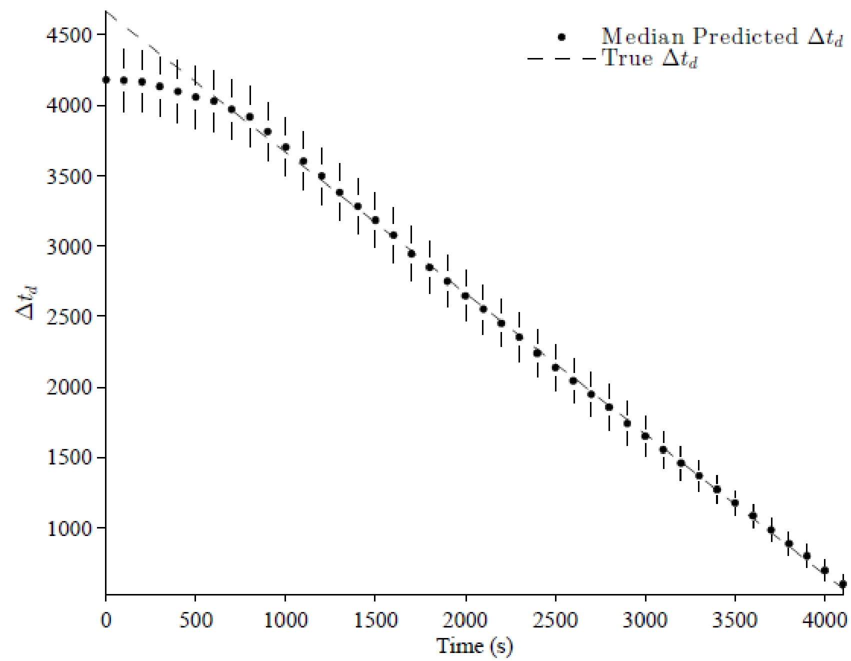
- Planetary rover testbed at NASA Ames Research Center
  - 24 lithium ion batteries, two parallel sets of 12 in series
  - Batteries power 4 motors, one for each wheel (skid steering)
- Rover operated in two driving modes
  - Unstructured driving
    - Rover is driven freely by an operator, without prior knowledge of actions
  - Structured driving
    - Rover has a given mission, to visit a set of waypoints
    - Rover moves along, visiting waypoints
    - End-of-discharge prediction is required in order to ensure the given set of waypoints can be visited, and if not, to replan the route to optimize mission value



Ref : A. Sweet et al "Demonstration of Prognostics-Enabled Decision Making Algorithms on a Hardware Mobile Robot Test Platform", PHM 2013

Results: Structured Driving





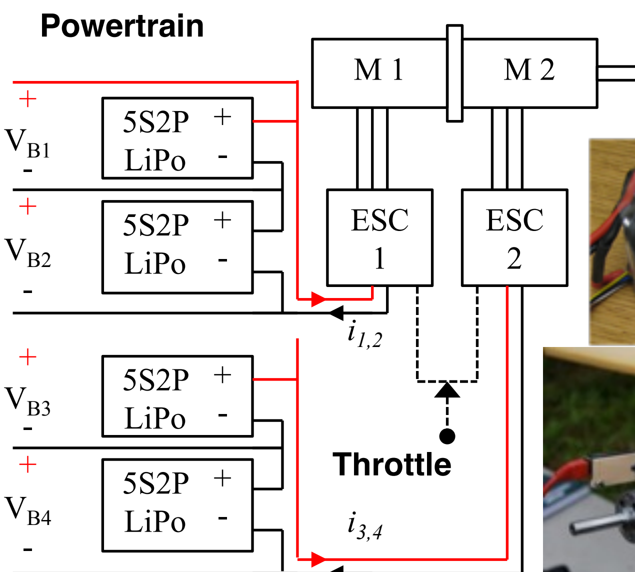
Predictions are very accurate since rover travels at a known fixed average speed, and waypoints are known.

Uncertainty in predictions is *significantly less than* for unstructured driving, since more information about future inputs are known.

Predictions are under at the start because power drawn for first 500 s is half the average.

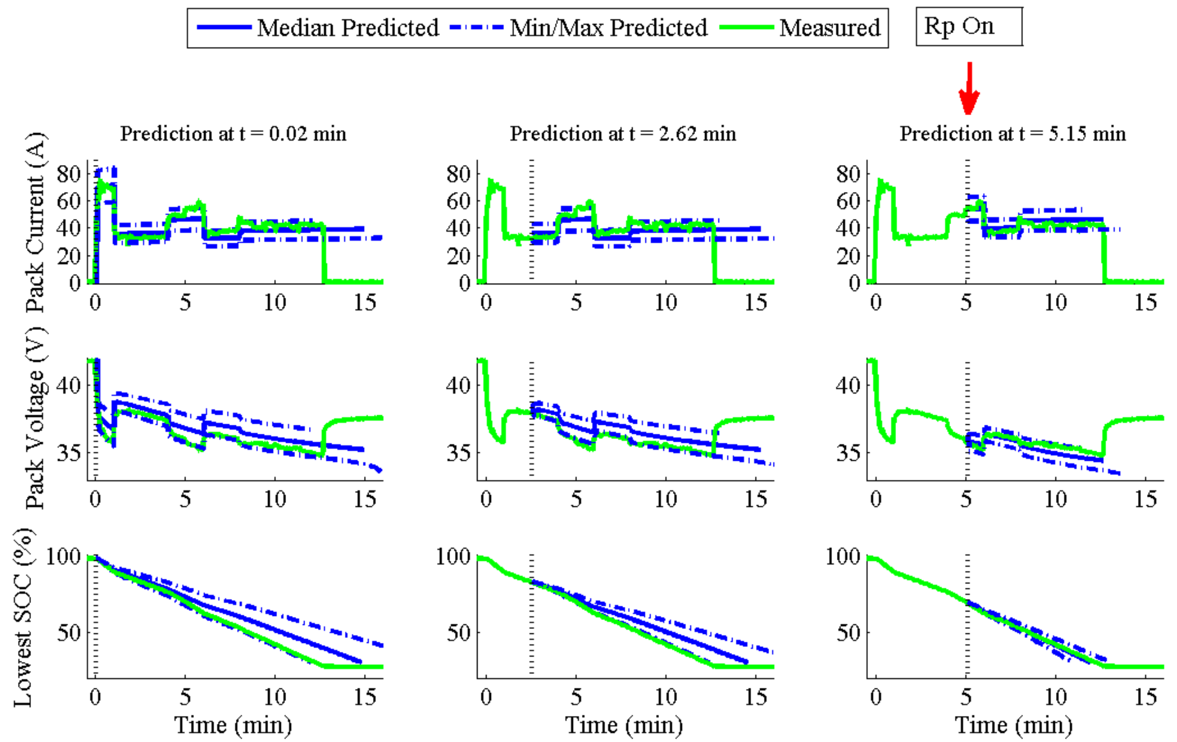
Edge 540-T

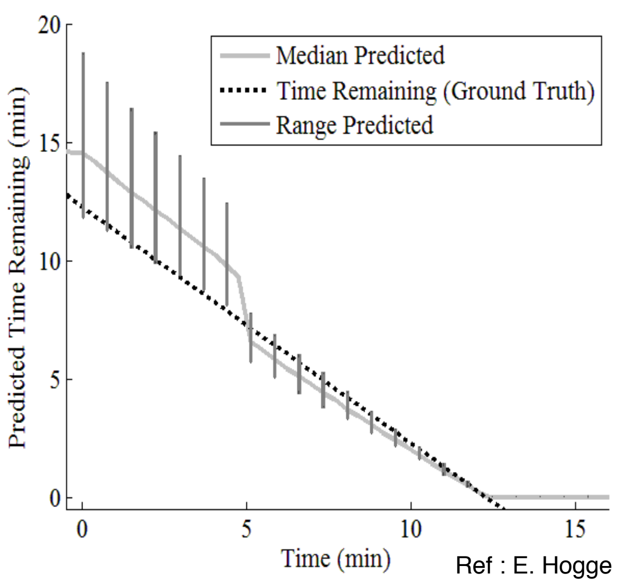
- Subscale electric aircraft operated at NASA Langley Research Center
- Powered by four sets of Li-polymer batteries
- Estimate SOC online and provide EOD and remaining flight time predictions for ground-based pilots



Predication over Flight Plan

- Measured and predicted battery current, voltage and SOC different time steps
- The min, max and median predictions are plotted from each sample time until the predicated SOC reaches 30%



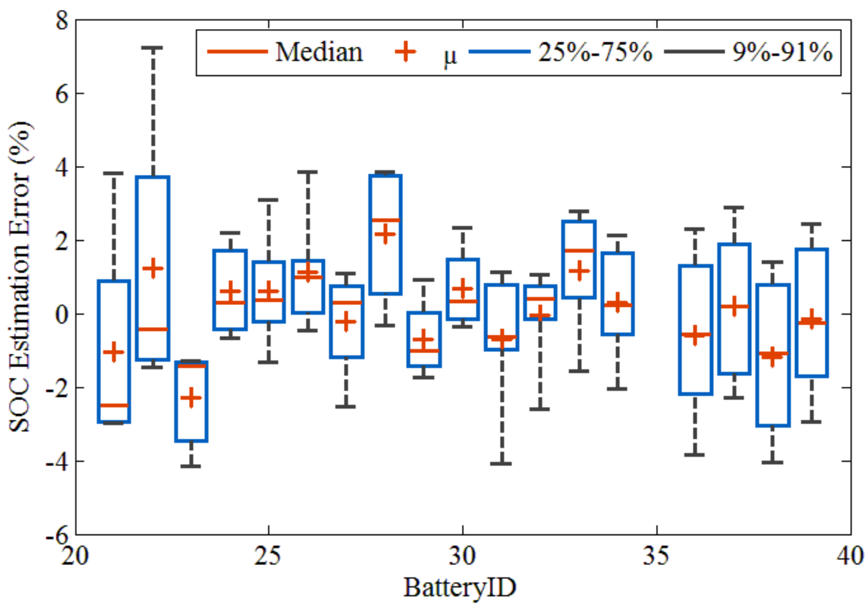


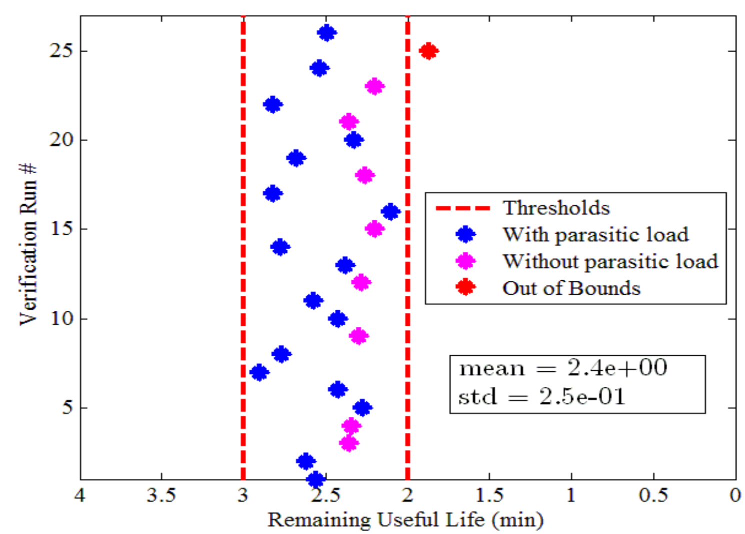
- Predictions for remaining flight time for entire flight plan
- Overestimate till parasitic load is injected
- Once the parasitic load is detected the remaining flying time time prediction shifts down.

Ref : E. Hogge et al, “Verification of a Remaining Flying Time Prediction System for Small Electric Aircraft”, PHM 2015

Performance Requirements

- Accuracy requirements for the two minute warning were specified as:
  - *The prognostic algorithm shall raise an alarm no later than two minutes before the lowest battery SOC estimate falls below 30% for at least 90% of verification trial runs.*
  - *The prognostic algorithm shall raise an alarm no earlier than three minutes before the lowest battery SOC estimate falls below 30% for at least 90% of verification trial runs.*
  - *Verification trial statistics must be computed using at least 20 experimental runs*





Data Sets Available for Download

- https://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/

Randomized Battery Usage Data Set
Publications using this data set

Description	Batteries are continuously cycled with randomly generated current profiles. Reference charging and discharging cycles are also performed after a fixed interval of randomized usage in order to provide reference benchmarks for battery state of health.
Format	
Datasets	+ Download Randomized Battery Usage Data Set 1 (1285 downloads) + Download Randomized Battery Usage Data Set 2 (936 downloads) + Download Randomized Battery Usage Data Set 3 (906 downloads) + Download Randomized Battery Usage Data Set 4 (4217 downloads) + Download Randomized Battery Usage Data Set 5 (825 downloads) + Download Randomized Battery Usage Data Set 6 (890 downloads) + Download Randomized Battery Usage Data Set 7 (857 downloads)
Dataset Citation	B. Bole, C. Kulkarni, and M. Daigle "Randomized Battery Usage Data Set", NASA Ames Prognostics Data Repository (http://ti.arc.nasa.gov/project/prognostic-data-repository), NASA Ames Research Center, Moffett Field, CA
Publication Citation	B. Bole, C. Kulkarni, and M. Daigle, 'Adaptation of an Electrochemistry-based Li-Ion Battery Model to Account for Deterioration Observed Under Randomized Use', Annual Conference of the Prognostics and Health Management Society, 2014

HIRF Battery Data Set
Publications using this data set

Description	Battery Data collected from the Experiments on the Edge 540 Aircraft in HIRF Chamber. Refernce document can be downloaded here
Format	The set is in .mat format and has been zipped.
Datasets	+ Download HIRF Battery Data Set 1 (184 downloads) + Download HIRF Battery Data Set 2 (127 downloads) + Download HIRF Battery Data Set 3 (131 downloads) + Download HIRF Battery Data Set 4 (125 downloads) + Download HIRF Battery Data Set 5 (149 downloads) + Download HIRF Battery Data Set 6 (135 downloads)
Dataset Citation	C. Kulkarni, E. Hogge, C. Quach and K. Goebel "HIRF Battery Data Set", NASA Ames Prognostics Data Repository (http://ti.arc.nasa.gov/project/prognostic-data-repository), NASA Ames Research Center, Moffett Field, CA
Publication Citation	Verification of a Remaining Flying Time Prediction System for Small Electric Aircraft. Edward F. Hogge, Brian M. Bole, Sixto L. Vazquez, Jose R., Annual Conference of the Prognostics and Health Management, PHM 2015

Remarks (1/2)

- Electrical and Electronics PHM Maturity - scientific and engineering challenges
- Research approach challenges
  - How to balance lack of knowledge of the system vs own expertise on particular PHM tools
  - Data-driven or model-based?
    - Data is always needed but more important, information about degradation/aging processes is key
    - Experiments and field data

Remarks (2/2)

- Aging systems as a research tool
  - Value in terms of exploration of precursors of failure and their measurements is evident
  - Still an open question on how degradation models and algorithms are translated to the real usage timescale
- In the use of physics
  - It should be embraced
- Validate models and algorithms with data from lab experiments and fielded systems
- A success in developing PHM methodologies in an real usage application will require the right team

Acknowledgments

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  - Kai Goebel, NASA Ames Research Center
  - Edward Hogge, Northrop Grumman Technology Services, NASA Langley
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  - Shankar Sankararaman, SGT, Inc., NASA Ames Research Center

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  - NASA Aviation Safety Program – IVHM Project
  - NASA SMART –NAS Project

Thank you